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Bouqata et al.

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(54) **COMPUTER-IMPLEMENTED SYSTEM WITH ADAPTIVE COGNITIVE FEATURES AND METHOD OF USING THE SAME**

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(51) **Int. Cl.**
G06F 15/18 (2006.01)
G06N 99/00 (2010.01)

(52) **U.S. Cl.**
CPC ***G06N 99/005*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 15/18; G06N 99/005; G06N 5/027; G06N 5/025
USPC 706/12
See application file for complete search history.

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Assistant Examiner — Kevin W Figueroa
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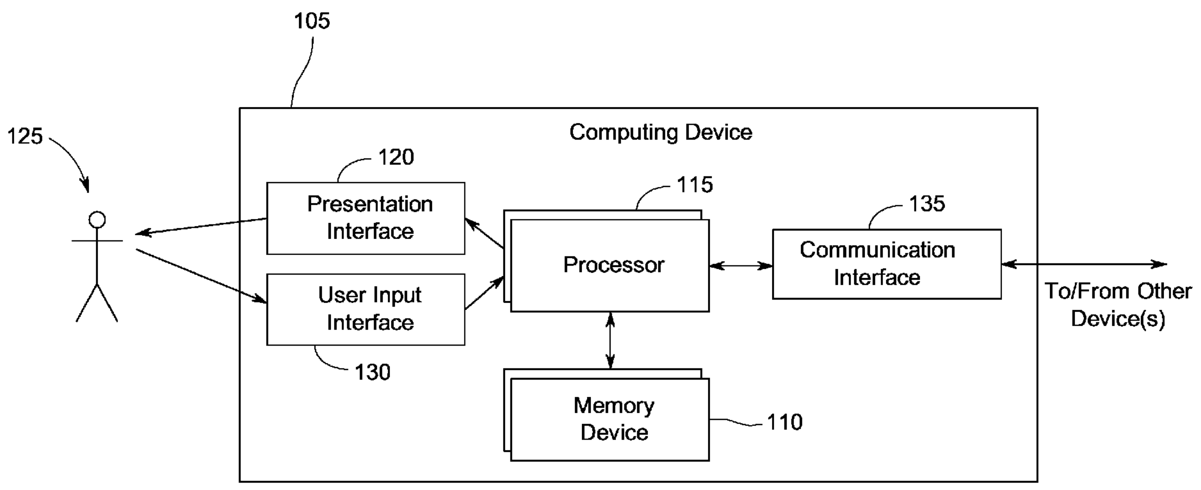
(57) **ABSTRACT**

A computer-implemented system includes an edge module and at least one input device coupled to the edge module. The at least one input device is configured to generate data input signals. The system also includes a cognitive module coupled to the edge module. The cognitive module includes a perception sub-module coupled to the edge module. The perception sub-module is configured to receive the data input signals. The cognitive module also includes a learning sub-module coupled to the perception sub-module. The learning sub-module is configured to adaptively learn at least in part utilizing the data input signals.

12 Claims, 20 Drawing Sheets



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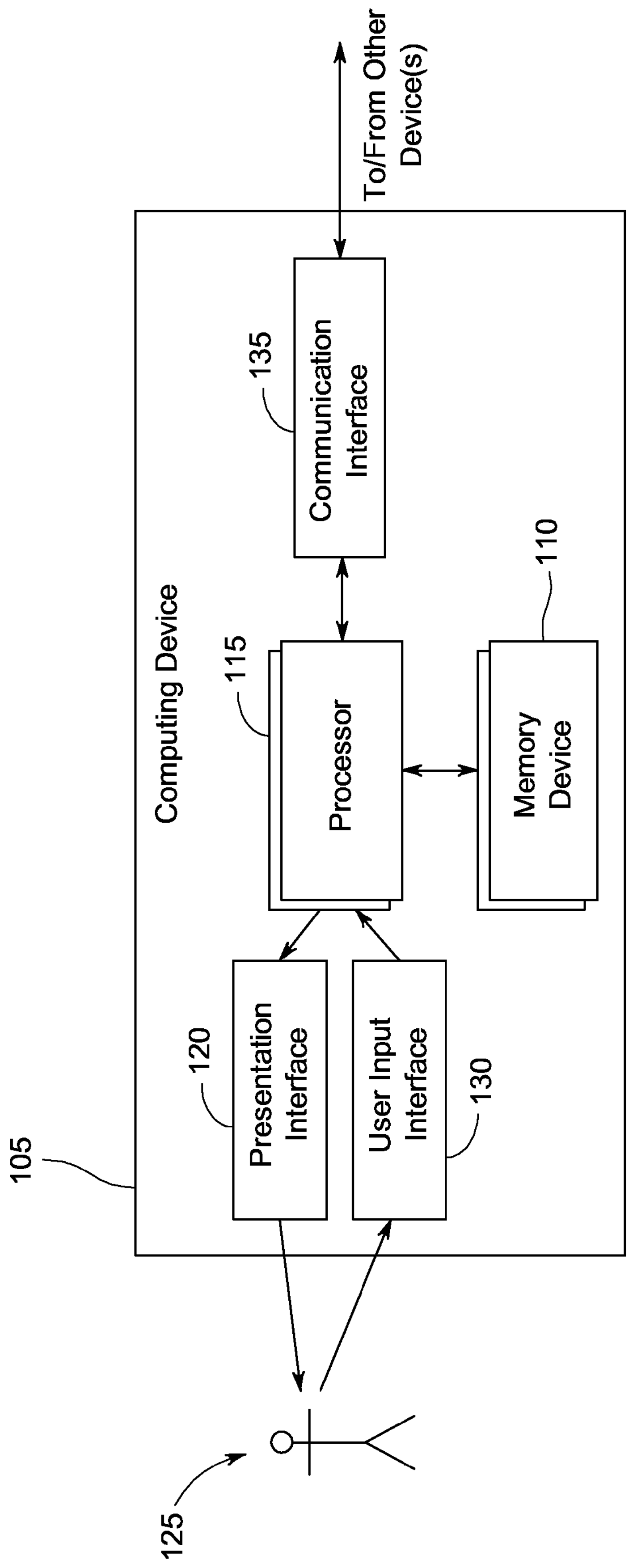
To/From Other Device(s)
Computing Device
105
135
Communication Interface
115
Processor
110
Memory Device
120
Presentation Interface
User Input Interface
130
125

FIG. 1

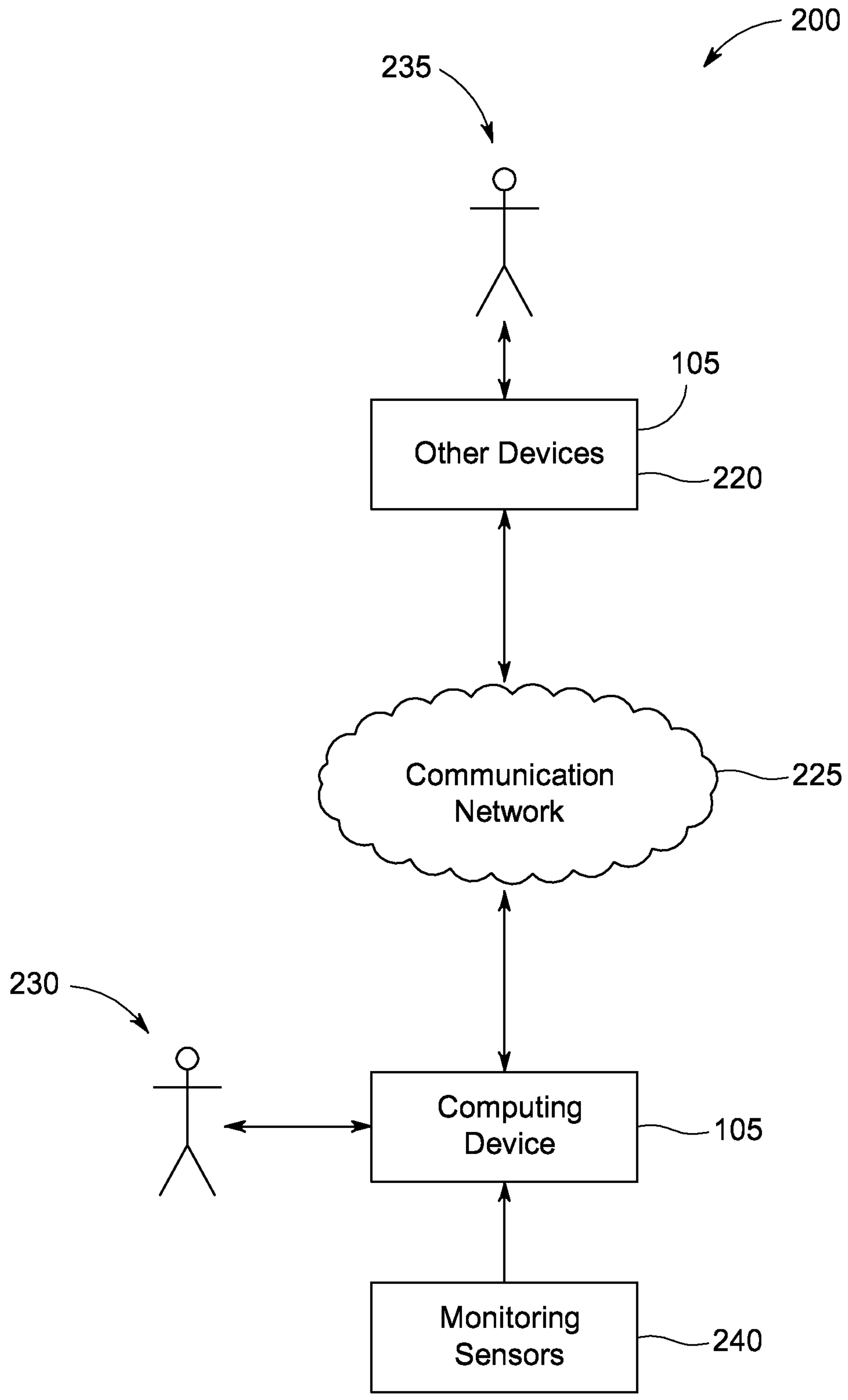
200
235
105
Other Devices
220
Communication Network
225
230
Computing Device
105
Monitoring Sensors
240

FIG. 2

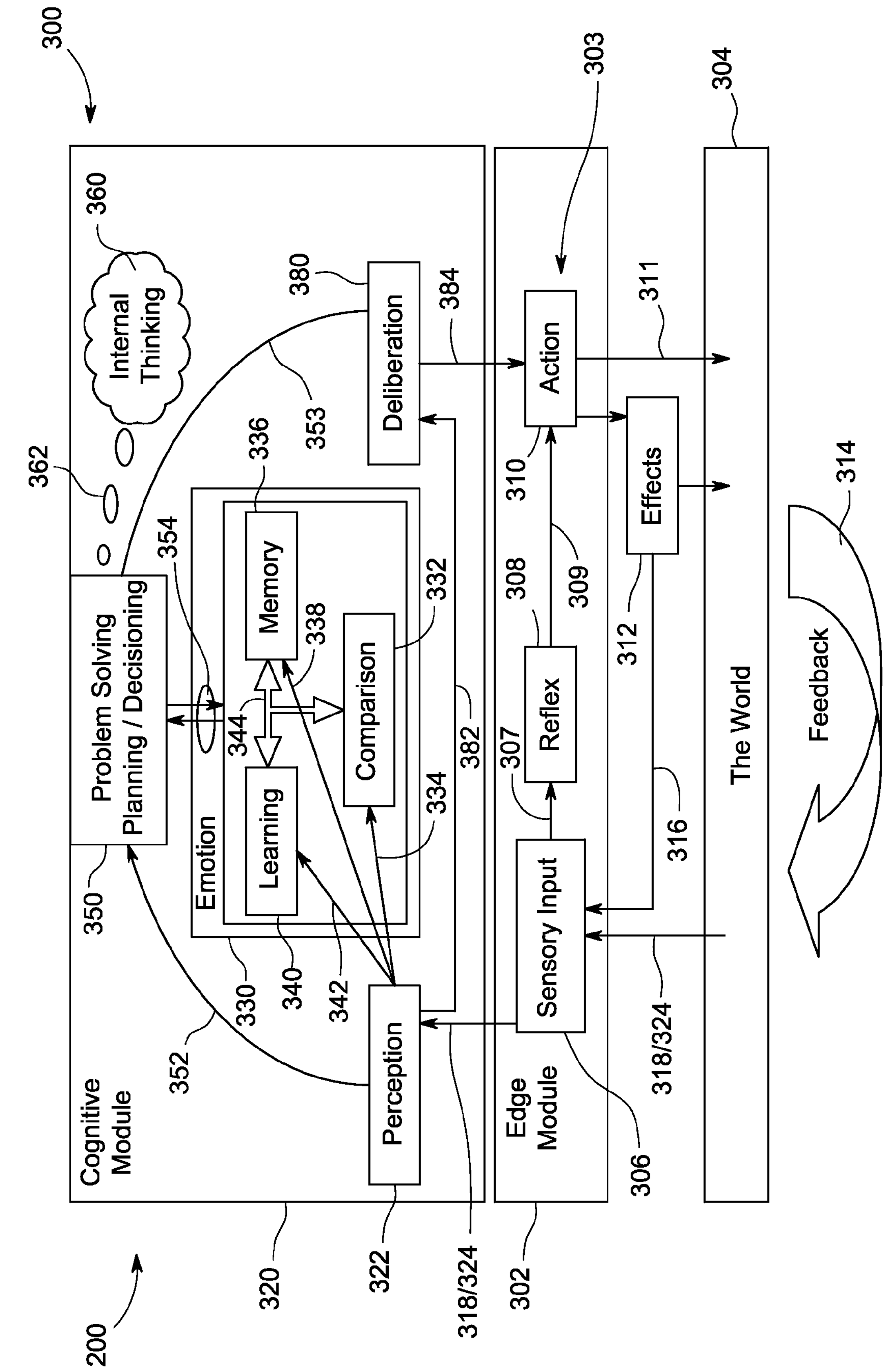
300
200
Cognitive Module
Perception
Emotion
Learning
Memory
Comparison
Problem Solving Planning / Decisioning
Internal Thinking
Deliberation
Edge Module
Sensory Input
Reflex
Action
Effects
The World
Feedback
302
303
304
306
307
308
309
310
311
312
314
316
318/324
318/324
320
322
330
332
334
336
338
340
342
344
350
352
353
354
360
362
380
382
384

FIG. 3

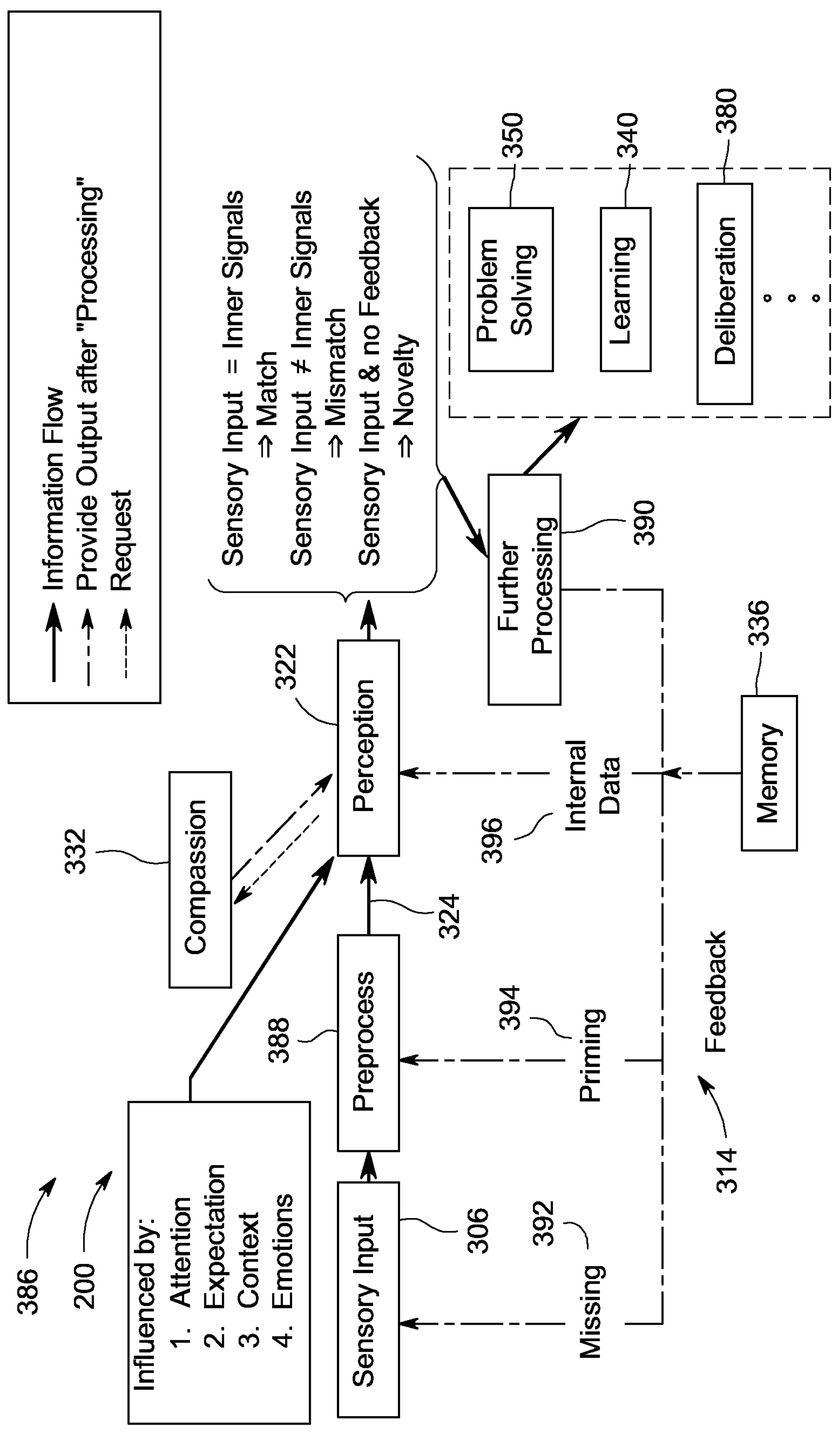
Information Flow
Provide Output after "Processing"
Request
Sensory Input = Inner Signals ⇒ Match
Sensory Input ≠ Inner Signals ⇒ Mismatch
Sensory Input & no Feedback ⇒ Novelty
350
340
380
Problem Solving
Learning
Deliberation
Further Processing
390
322
Perception
332
Compassion
324
396
Internal Data
Memory
336
386
200
Influenced by:
1. Attention
2. Expectation
3. Context
4. Emotions
388
Preprocess
394
Priming
Feedback
Sensory Input
306
392
Missing
314

FIG. 4

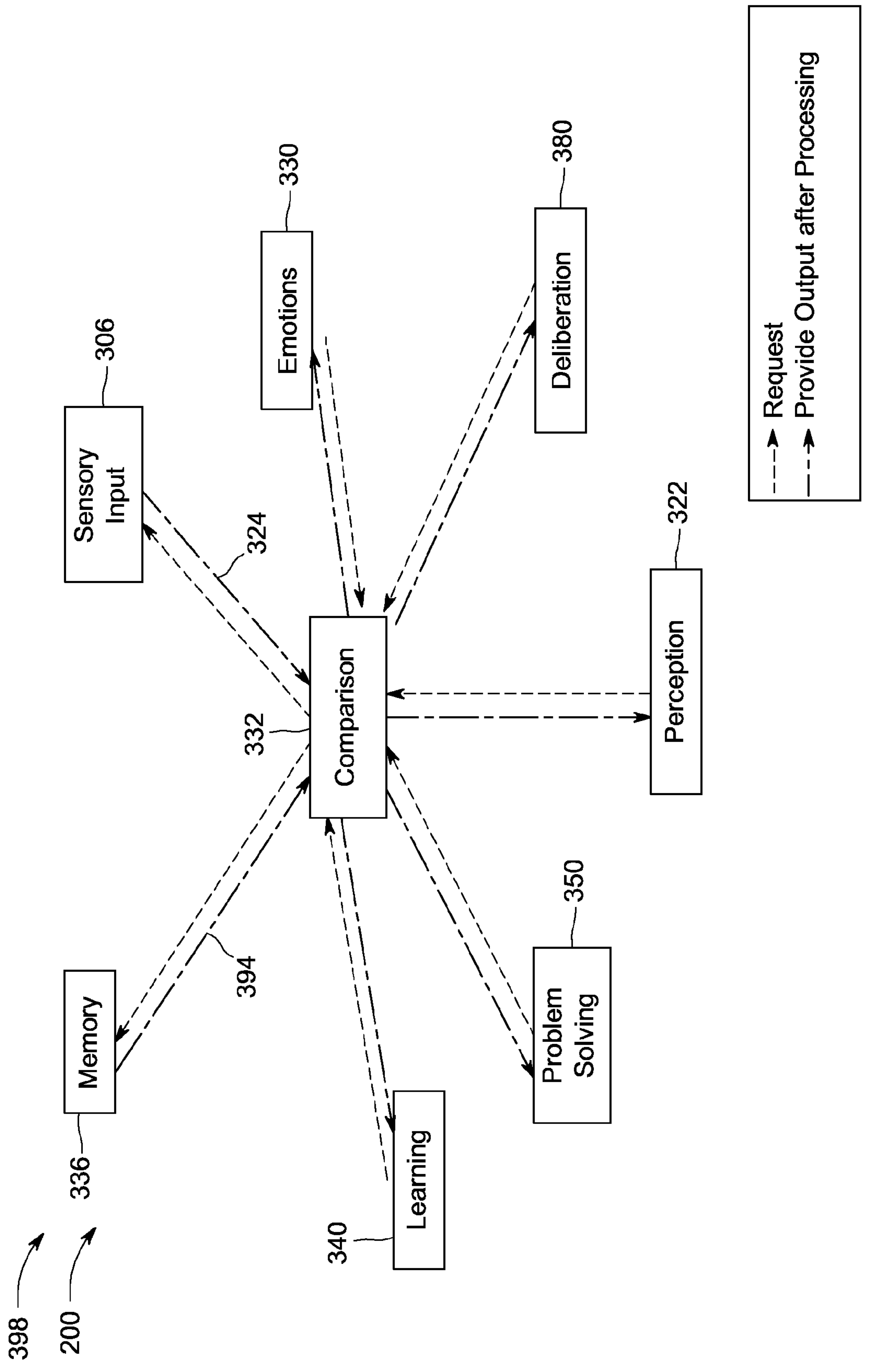
398
200
Memory
336
394
Learning
340
Problem Solving
350
Comparison
332
Sensory Input
306
324
Emotions
330
Deliberation
380
Perception
322
Request
Provide Output after Processing

FIG. 5

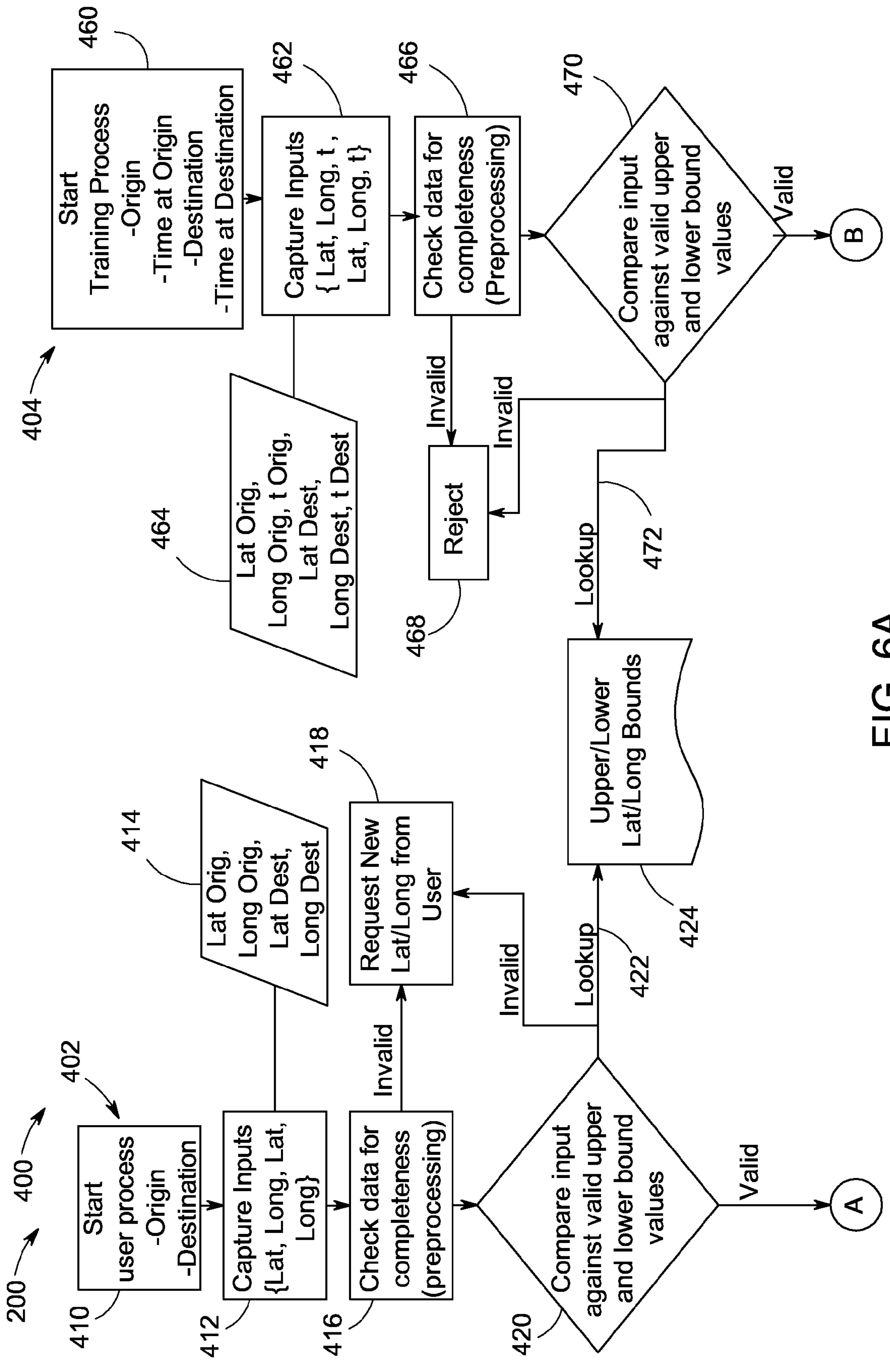
200
400
402
Start
user process
-Origin
-Destination
410
Capture Inputs
{Lat, Long, Lat, Long}
412
Lat Orig, Long Orig, Lat Dest, Long Dest
414
Check data for completeness (preprocessing)
416
Invalid
Request New Lat/Long from User
418
Compare input against valid upper and lower bound values
420
Valid
A
Invalid
Lookup
422
Upper/Lower Lat/Long Bounds
424
404
Start
Training Process
-Origin
-Time at Origin
-Destination
-Time at Destination
460
Capture Inputs
{ Lat, Long, t , Lat, Long, t}
462
Lat Orig, Long Orig, t Orig, Lat Dest, Long Dest, t Dest
464
Check data for completeness (Preprocessing)
466
Invalid
Reject
468
Invalid
Compare input against valid upper and lower bound values
470
Valid
B
Lookup
472

FIG. 6A

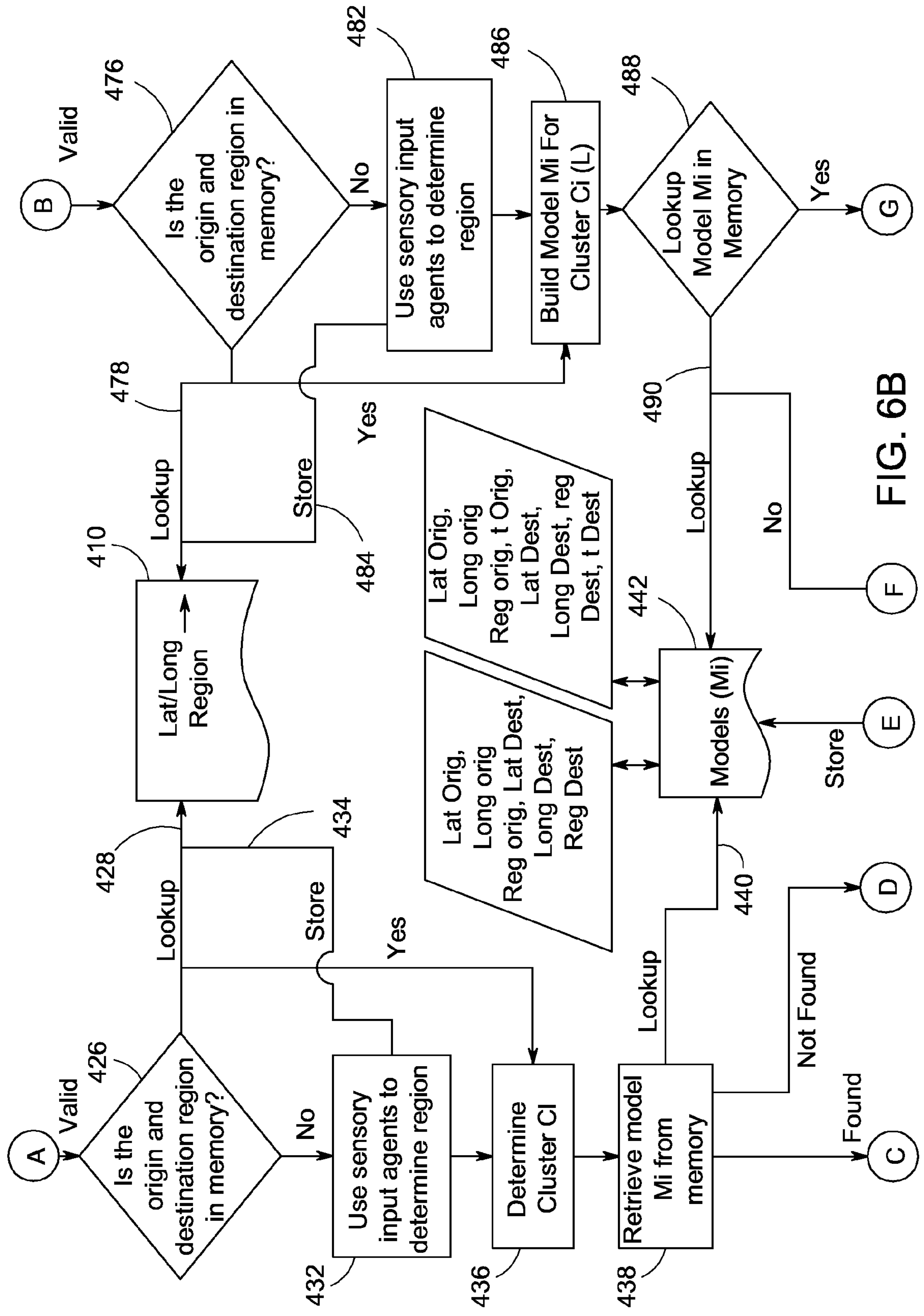
A
Valid
426
Is the origin and destination region in memory?
No
432
Use sensory input agents to determine region
436
Determine Cluster CI
438
Retrieve model Mi from memory
Found
C
Not Found
D
Lookup
440
428
Lookup
434
Store
Yes
410
Lat/Long → Region
B
Valid
476
Is the origin and destination region in memory?
No
482
Use sensory input agents to determine region
486
Build Model Mi For Cluster Ci (L)
488
Lookup Model Mi in Memory
Yes
G
478
Lookup
Store
484
Yes
Lat Orig, Long orig Reg orig, Lat Dest, Long Dest, Reg Dest
Lat Orig, Long orig Reg orig, t Orig, Lat Dest, Long Dest, reg Dest, t Dest
442
Models (Mi)
Store
E
490
Lookup
No
F

FIG. 6B

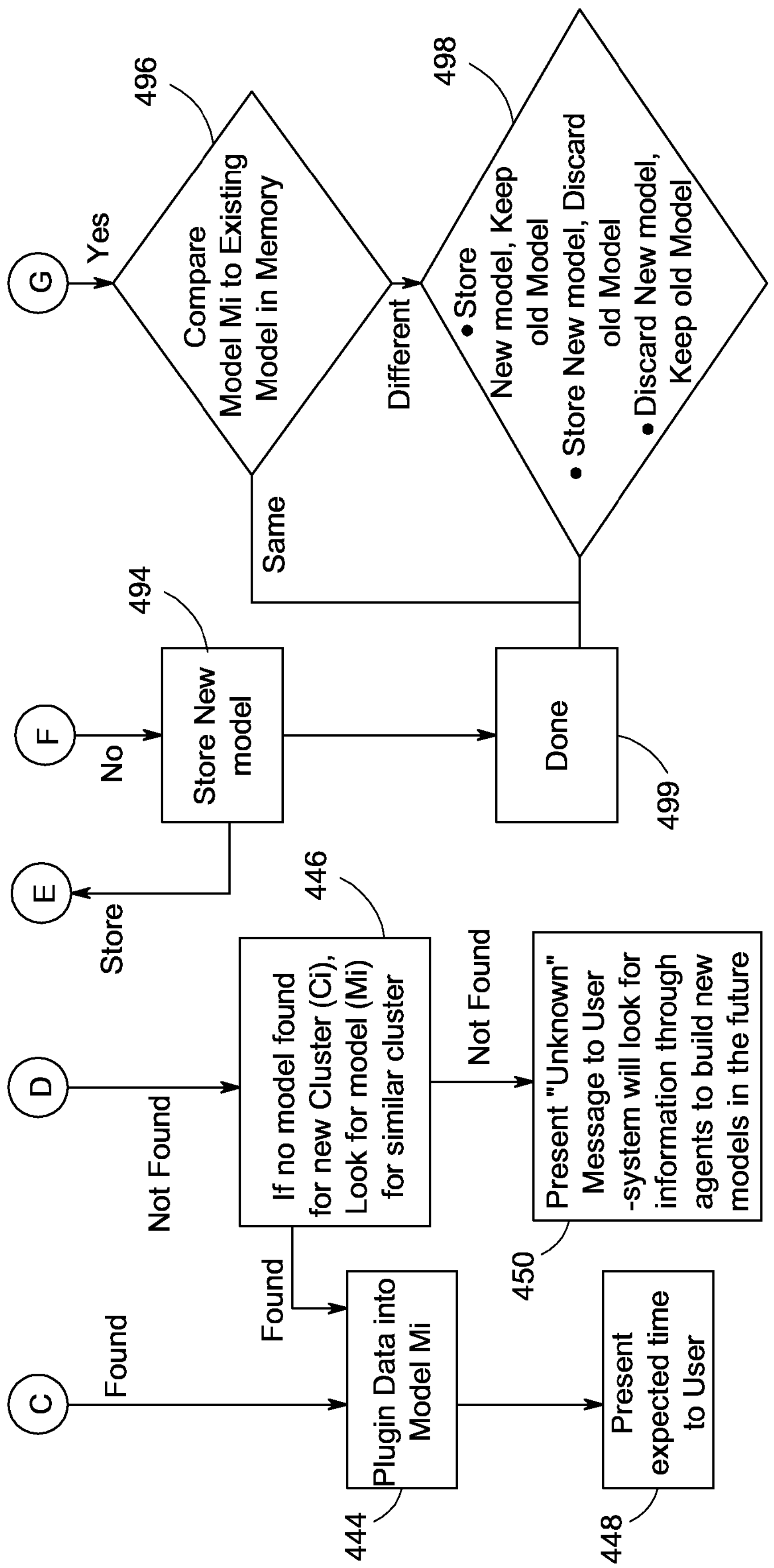
G
Yes
Compare Model Mi to Existing Model in Memory
496
Different
Same
• Store New model, Keep old Model
• Store New model, Discard old Model
• Discard New model, Keep old Model
498
F
No
Store New model
494
Done
499
E
Store
D
Not Found
If no model found for new Cluster (Ci), Look for model (Mi) for similar cluster
446
Not Found
Present "Unknown" Message to User -system will look for information through agents to build new models in the future
450
C
Found
Found
Plugin Data into Model Mi
444
Present expected time to User
448

FIG. 6C

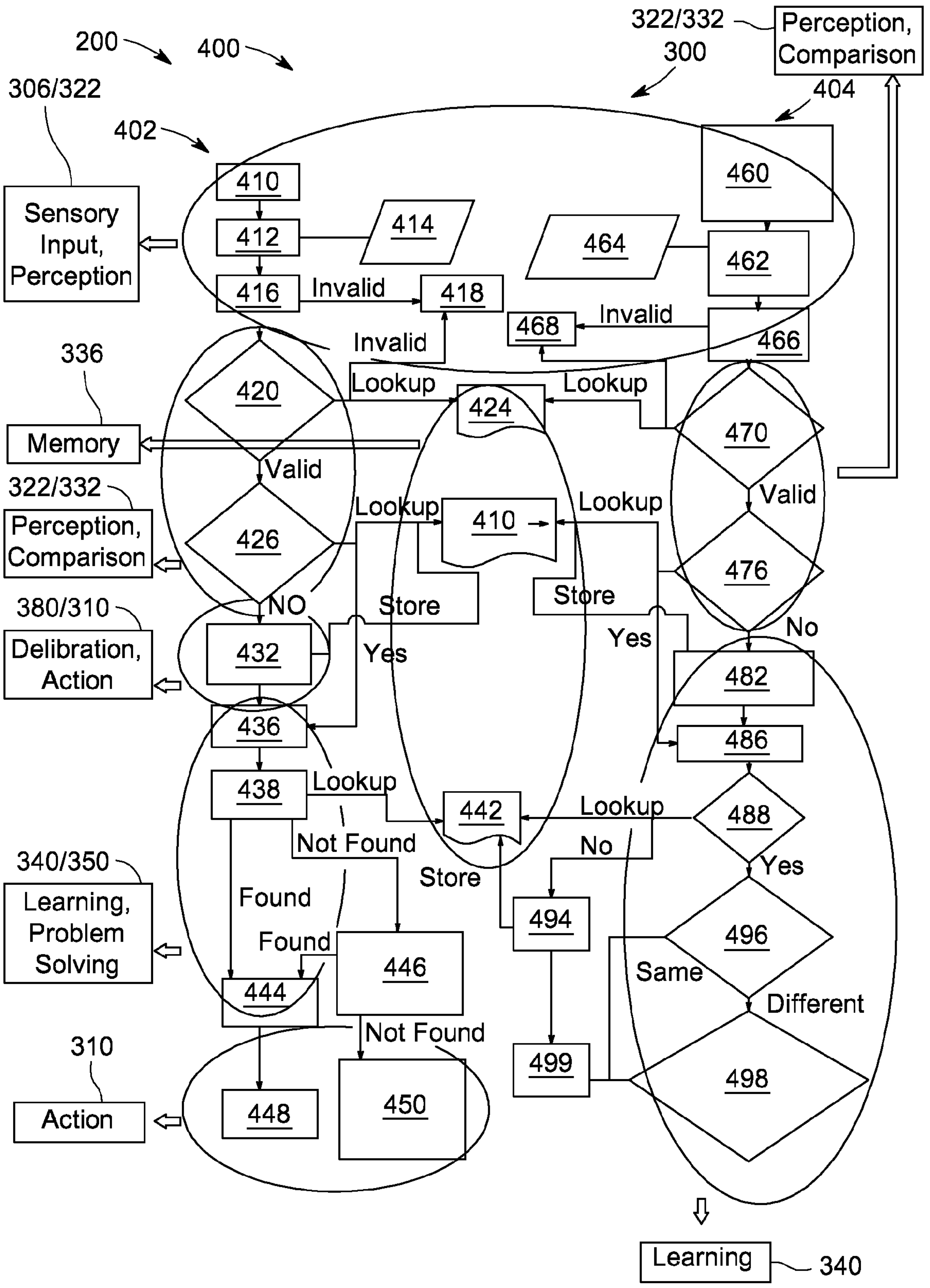
200
400
322/332
300
Perception, Comparison
404
306/322
402
410
412
414
460
464
462
Sensory Input, Perception
416
Invalid
418
468
Invalid
466
336
Invalid
420
Lookup
424
Lookup
470
Memory
Valid
Valid
322/332
Perception, Comparison
Lookup
410
Lookup
426
476
Store
Store
380/310
NO
No
Yes
Delibration, Action
432
Yes
482
436
486
Lookup
438
442
Lookup
488
Not Found
No
340/350
Store
Yes
Found
494
Learning, Problem Solving
Found
446
496
Same
444
Different
310
Not Found
499
498
450
Action
448
Learning
340

FIG. 7

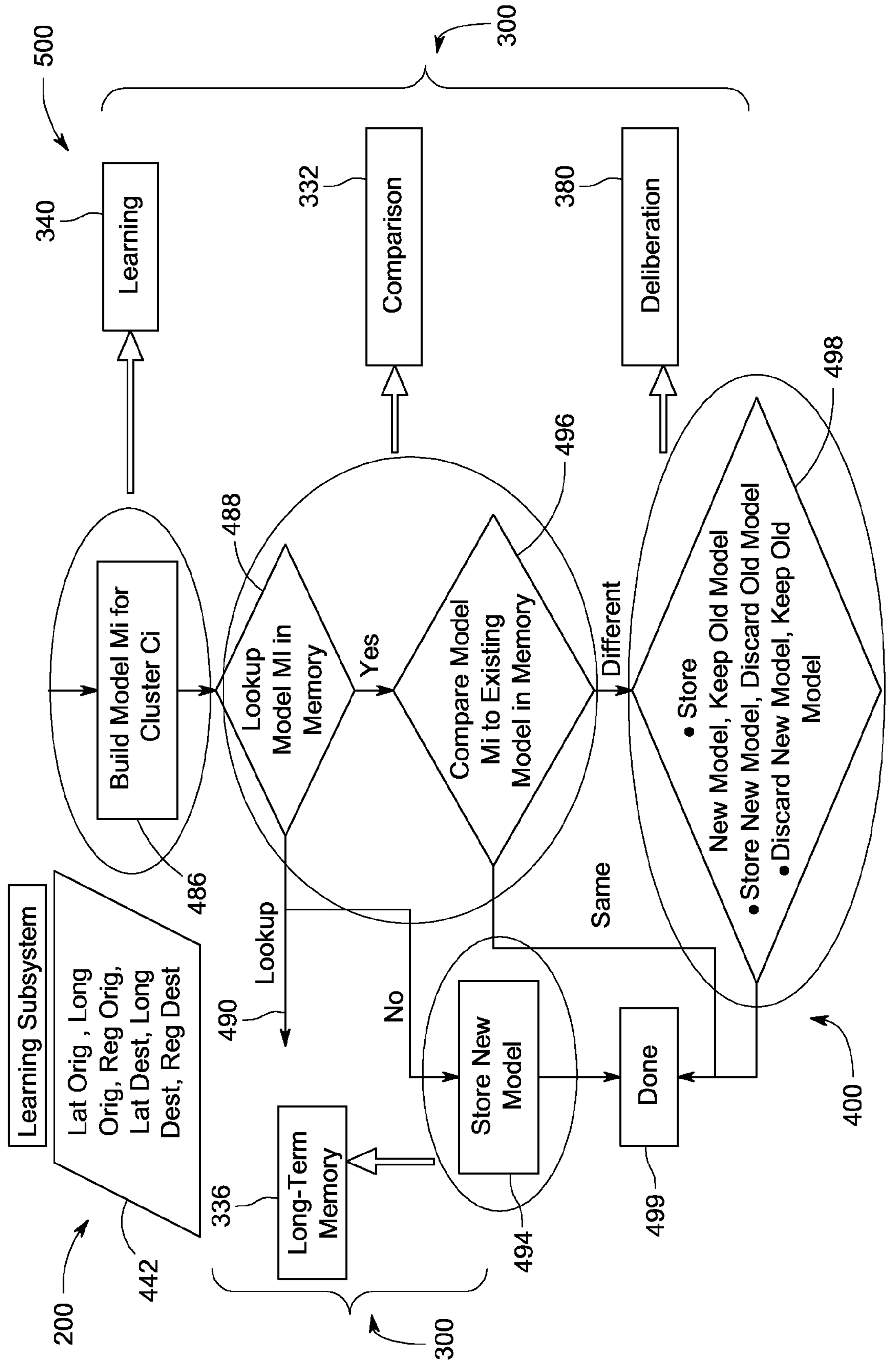
500
300
340
Learning
332
Comparison
380
Deliberation
488
496
498
Build Model Mi for Cluster Ci
Lookup Model Mi in Memory
Yes
Compare Model Mi to Existing Model in Memory
Different
• Store New Model, Keep Old Model
• Store New Model, Discard Old Model
• Discard New Model, Keep Old Model
Same
Learning Subsystem
Lat Orig , Long Orig, Reg Orig, Lat Dest, Long Dest, Reg Dest
486
Lookup
490
No
Store New Model
Done
400
336
Long-Term Memory
494
499
442
200
300

FIG. 8

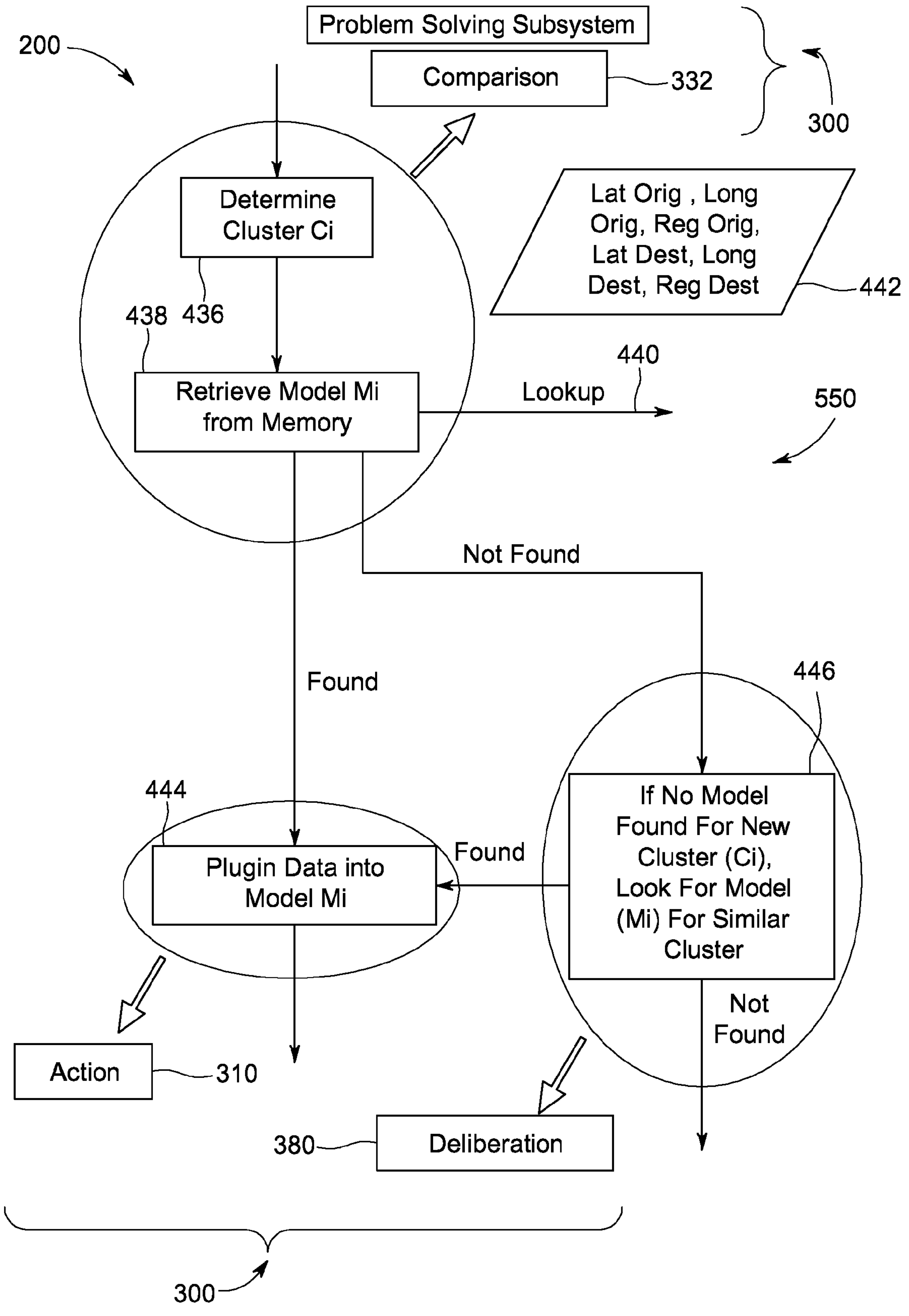
200
Problem Solving Subsystem
Comparison
332
300
Determine Cluster Ci
436
438
Lat Orig , Long Orig, Reg Orig, Lat Dest, Long Dest, Reg Dest
442
Retrieve Model Mi from Memory
440
Lookup
550
Not Found
Found
446
444
Plugin Data into Model Mi
Found
If No Model Found For New Cluster (Ci), Look For Model (Mi) For Similar Cluster
Not Found
Action
310
380
Deliberation
300

FIG. 9

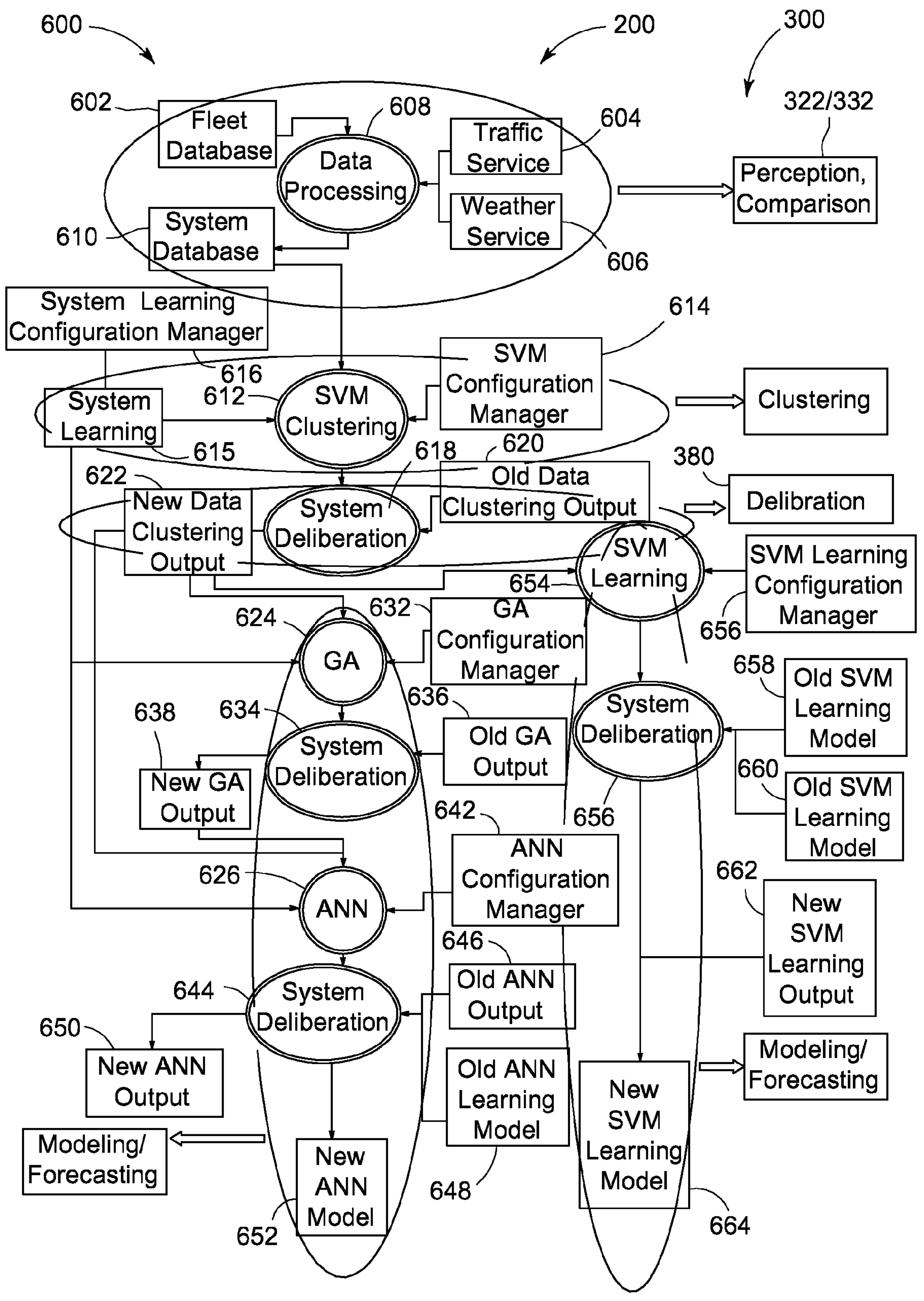
600
200
300
602
Fleet Database
608
Data Processing
Traffic Service
604
Weather Service
606
610
System Database
322/332
Perception, Comparison
System Learning Configuration Manager
616
614
SVM Configuration Manager
System Learning
612
SVM Clustering
Clustering
615
618
620
380
622
Old Data Clustering Output
Delibration
New Data Clustering Output
System Deliberation
SVM Learning
SVM Learning Configuration Manager
654
656
632
624
GA
GA Configuration Manager
658
Old SVM Learning Model
636
638
634
System Deliberation
Old GA Output
New GA Output
System Deliberation
656
660
Old SVM Learning Model
642
626
ANN
ANN Configuration Manager
662
New SVM Learning Output
646
644
System Deliberation
Old ANN Output
650
New ANN Output
Modeling/ Forecasting
Old ANN Learning Model
New SVM Learning Model
Modeling/ Forecasting
New ANN Model
648
652
664

FIG. 10

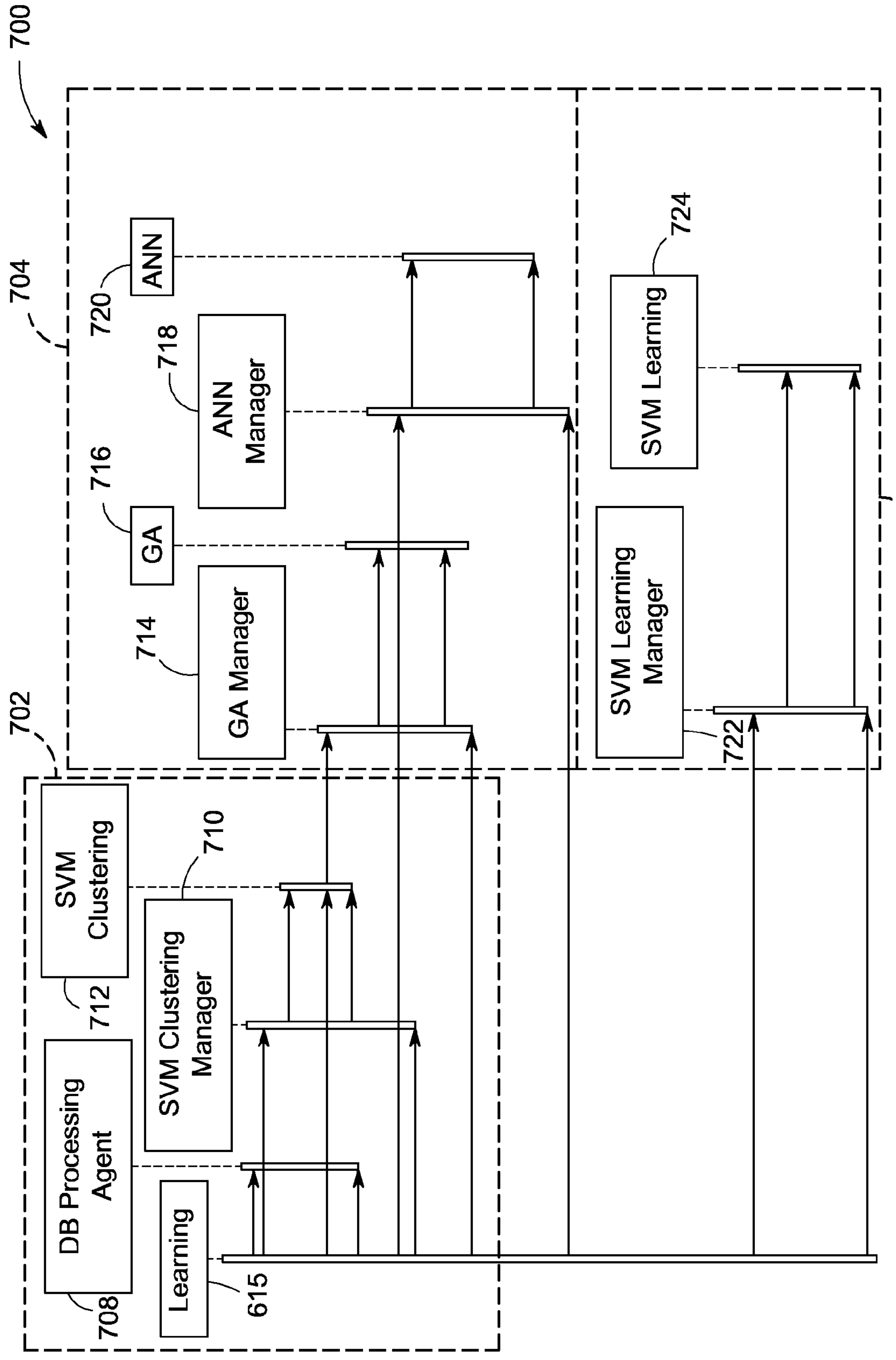
700
702
704
706
DB Processing Agent
708
Learning
615
SVM Clustering Manager
710
SVM Clustering
712
GA Manager
714
GA
716
ANN Manager
718
ANN
720
SVM Learning Manager
722
SVM Learning
724

FIG. 11

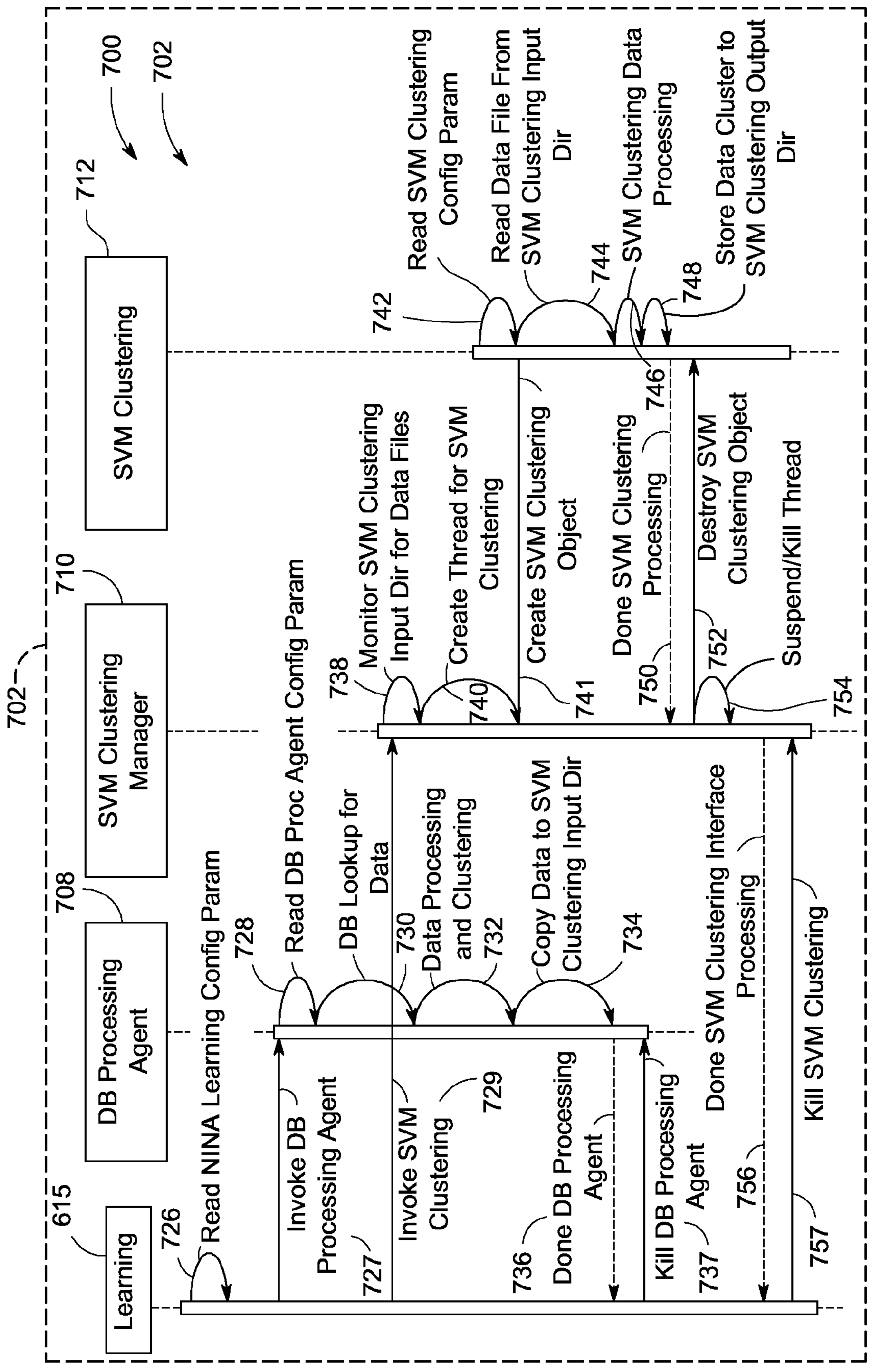
700
702
702
615
Learning
708
DB Processing Agent
710
SVM Clustering Manager
712
SVM Clustering
726
Read NINA Learning Config Param
Invoke DB Processing Agent
727
728
Read DB Proc Agent Config Param
DB Lookup for Data
730
Data Processing and Clustering
732
Copy Data to SVM Clustering Input Dir
734
Invoke SVM Clustering
729
Done DB Processing Agent
736
Kill DB Processing Agent
737
Done SVM Clustering Interface Processing
756
Kill SVM Clustering
757
738
Monitor SVM Clustering Input Dir for Data Files
740
Create Thread for SVM Clustering
Create SVM Clustering Object
741
Done SVM Clustering Processing
750
Destroy SVM Clustering Object
752
Suspend/Kill Thread
754
742
Read SVM Clustering Config Param
Read Data File From SVM Clustering Input Dir
744
SVM Clustering Data Processing
746
748
Store Data Cluster to SVM Clustering Output Dir

FIG. 12

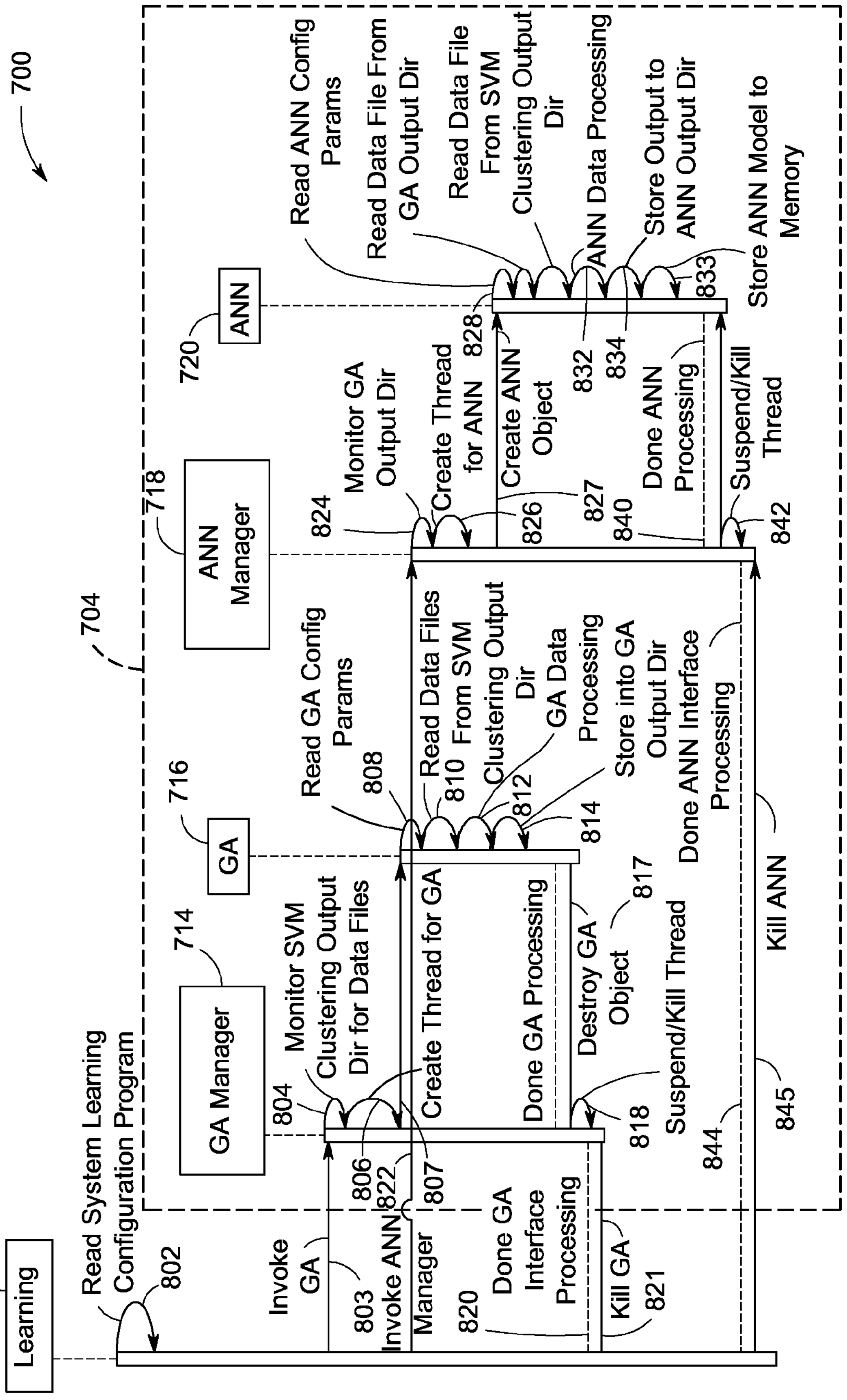
700
704
615
Learning
Read System Learning Configuration Program
802
Invoke GA
803
Invoke ANN Manager
820
Done GA Interface Processing
Kill GA
821
GA Manager
714
804
Monitor SVM Clustering Output Dir for Data Files
806
822
807
Create Thread for GA
Done GA Processing
Destroy GA Object
817
818
Suspend/Kill Thread
844
845
GA
716
Read GA Config Params
808
810
Read Data Files From SVM Clustering Output Dir
812
GA Data Processing
814
Store into GA Output Dir
Done ANN Interface Processing
Kill ANN
ANN Manager
718
824
Monitor GA Output Dir
Create Thread for ANN
826
827
840
Create ANN Object
Done ANN Processing
Suspend/Kill Thread
842
ANN
720
828
832
834
Read ANN Config Params
Read Data File From GA Output Dir
Read Data File From SVM Clustering Output Dir
ANN Data Processing
Store Output to ANN Output Dir
833
Store ANN Model to Memory

FIG. 13

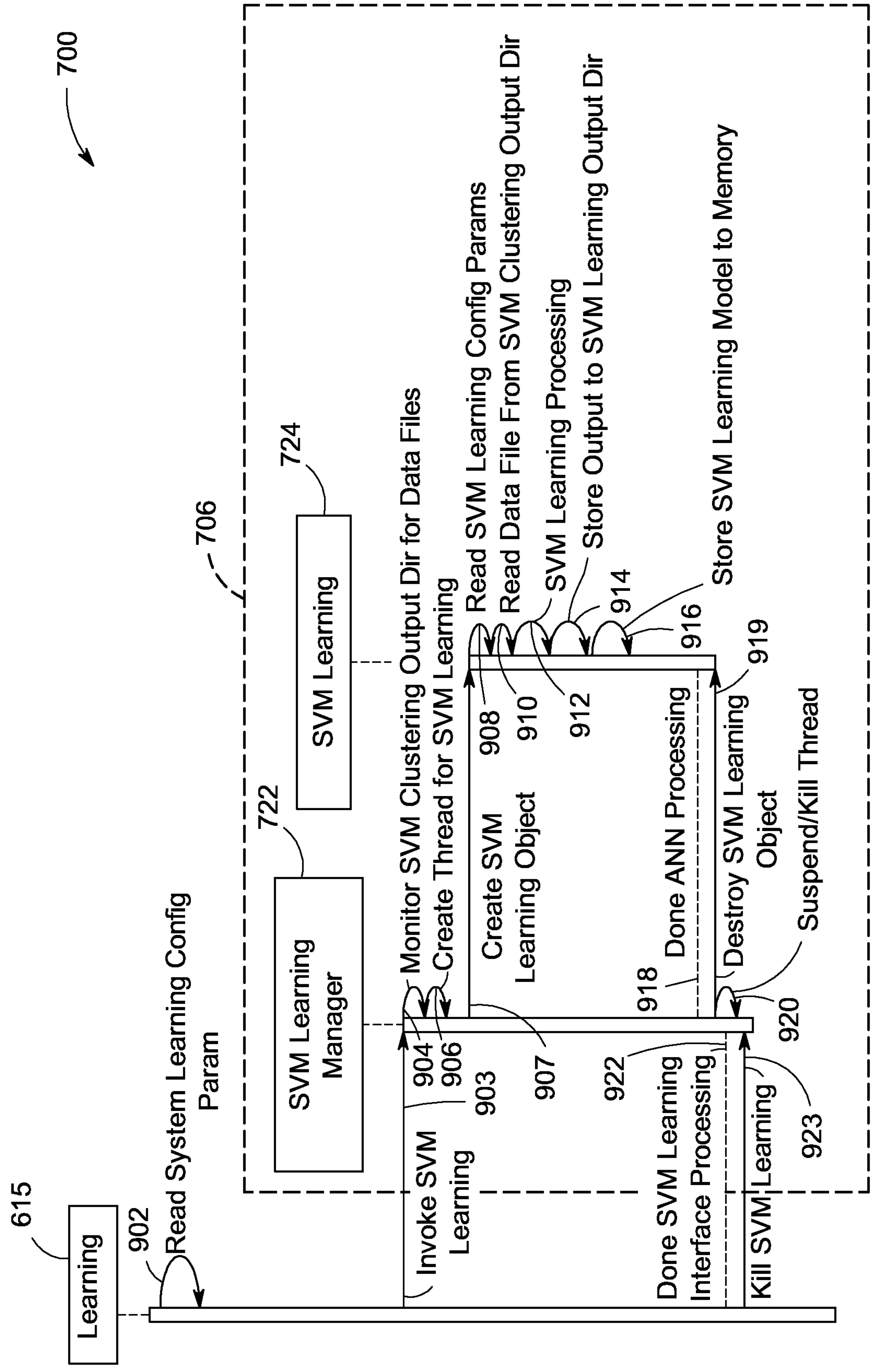
700
615
Learning
902
Read System Learning Config Param
706
SVM Learning Manager
722
SVM Learning
724
Invoke SVM Learning
903
904
906
907
Monitor SVM Clustering Output Dir for Data Files
Create Thread for SVM Learning
Create SVM Learning Object
908
910
912
914
916
Read SVM Learning Config Params
Read Data File From SVM Clustering Output Dir
SVM Learning Processing
Store Output to SVM Learning Output Dir
Store SVM Learning Model to Memory
918
Done ANN Processing
919
Destroy SVM Learning Object
920
Suspend/Kill Thread
922
Done SVM Learning Interface Processing
923
Kill SVM Learning

FIG. 14

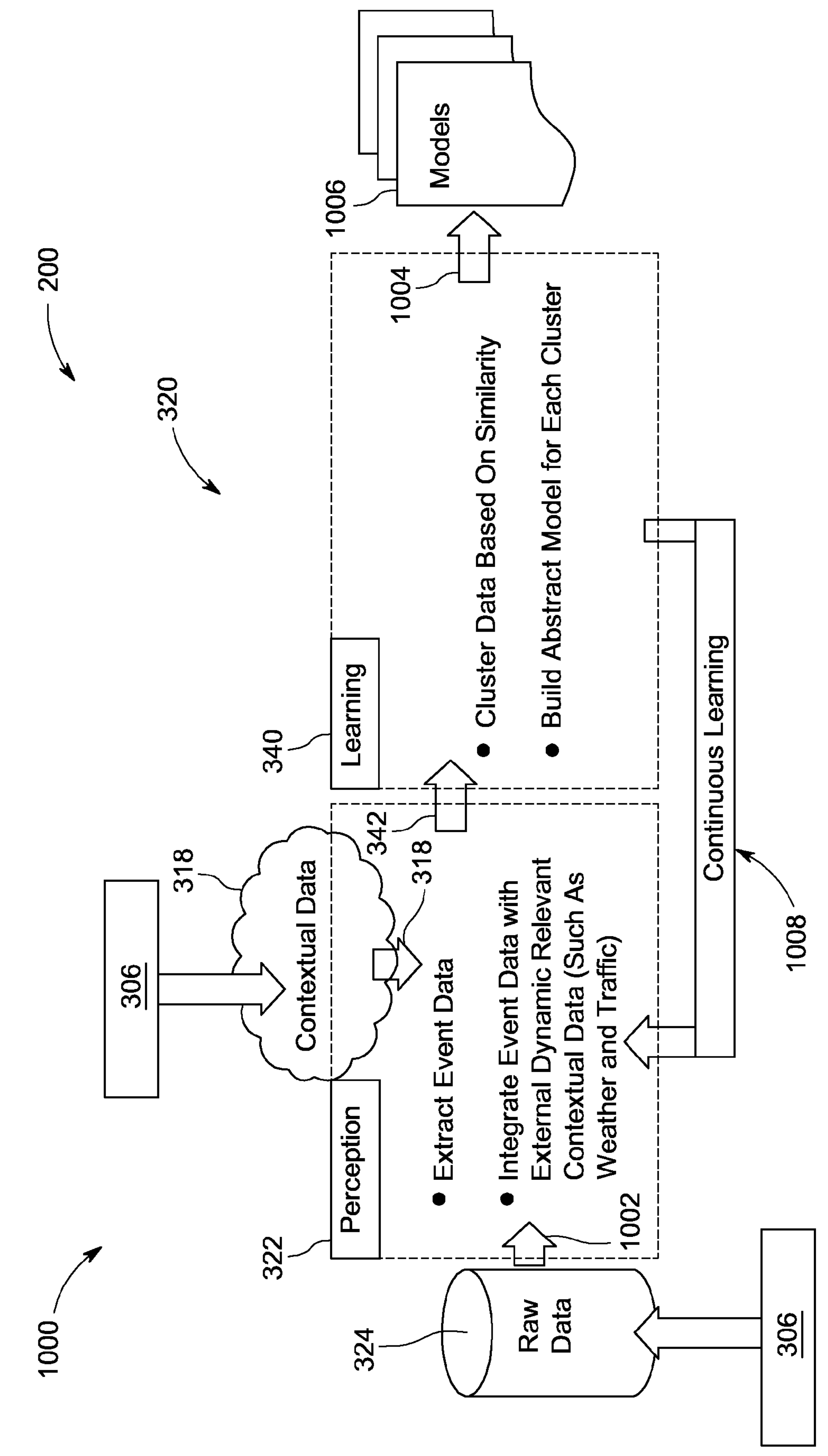
1000
200
320
306
318
Contextual Data
318
Perception
322
Extract Event Data
Integrate Event Data with External Dynamic Relevant Contextual Data (Such As Weather and Traffic)
1002
324
Raw Data
306
342
Learning
340
Cluster Data Based On Similarity
Build Abstract Model for Each Cluster
1004
1006
Models
Continuous Learning
1008

FIG. 15

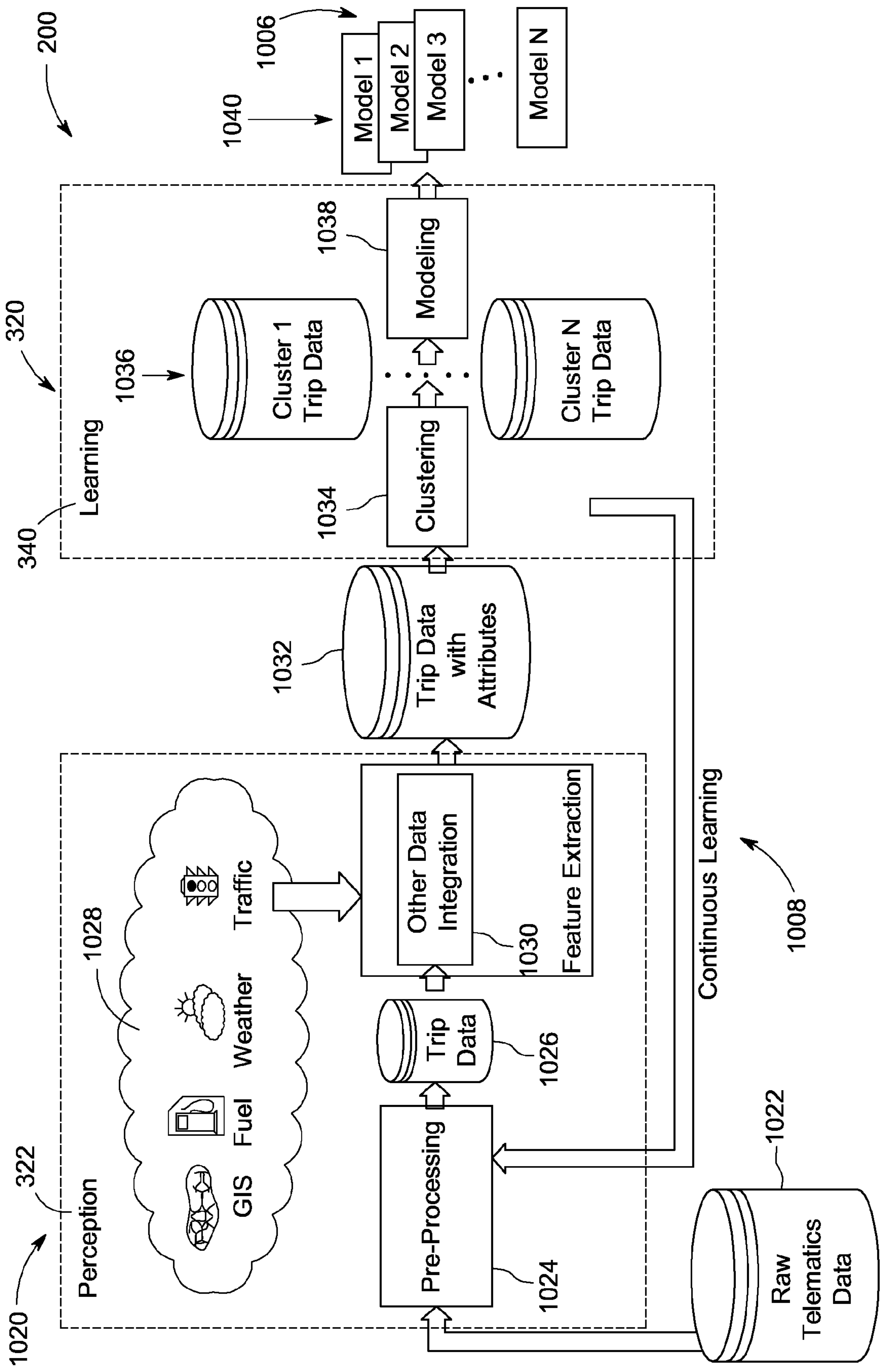
200
1020
322
Perception
GIS
Fuel
Weather
Traffic
1028
Pre-Processing
1024
Trip Data
1026
Other Data Integration
1030
Feature Extraction
Trip Data with Attributes
1032
340
Learning
320
Clustering
1034
Cluster 1 Trip Data
1036
Cluster N Trip Data
Modeling
1038
Model 1
Model 2
Model 3
Model N
1040
1006
Continuous Learning
1008
Raw Telematics Data
1022

FIG. 16

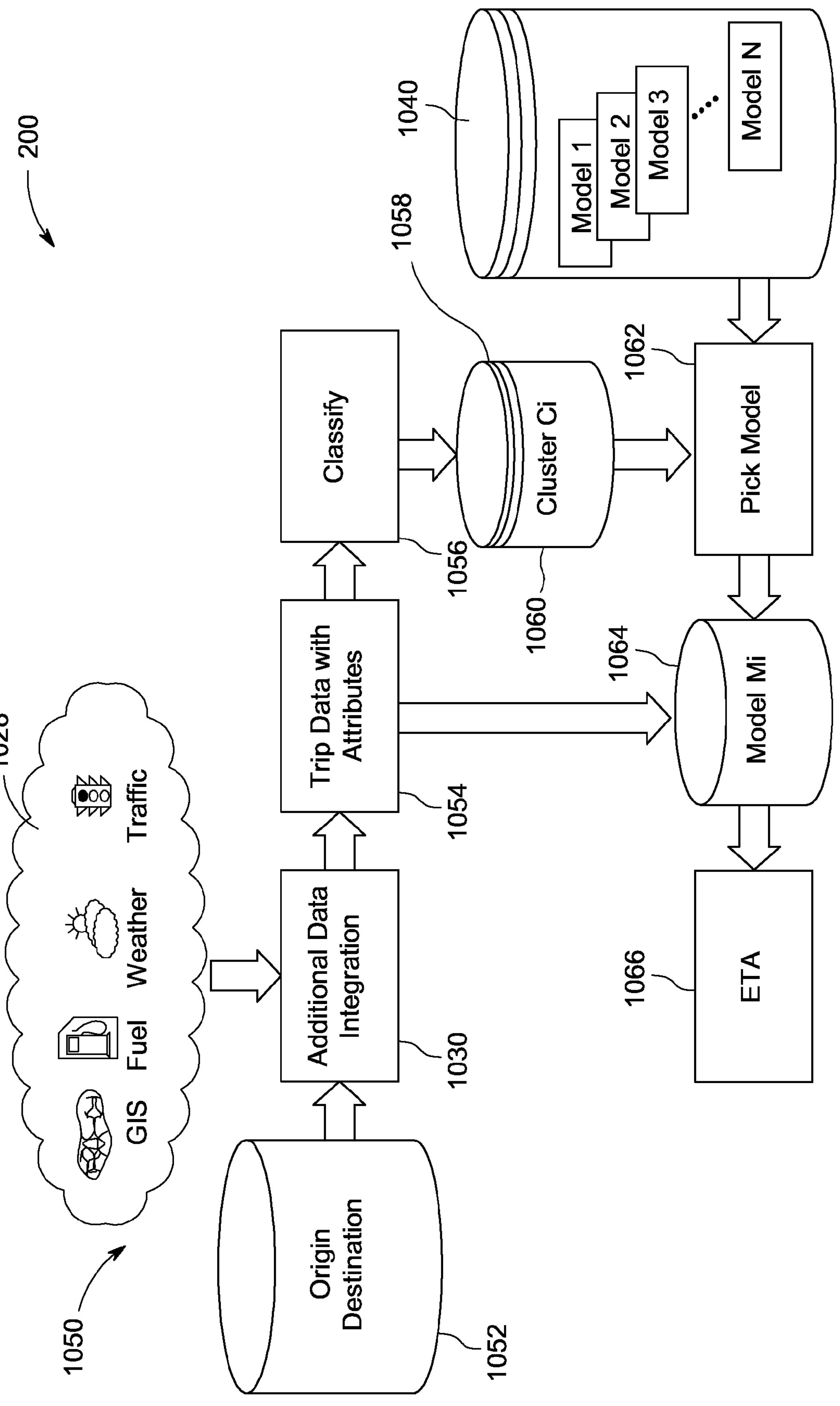
200
1050
1028
GIS
Fuel
Weather
Traffic
Origin Destination
1052
Additional Data Integration
1030
Trip Data with Attributes
1054
Classify
1056
1058
Cluster Ci
1060
Pick Model
1062
1040
Model 1
Model 2
Model 3
Model N
1064
Model Mi
1066
ETA

FIG. 17

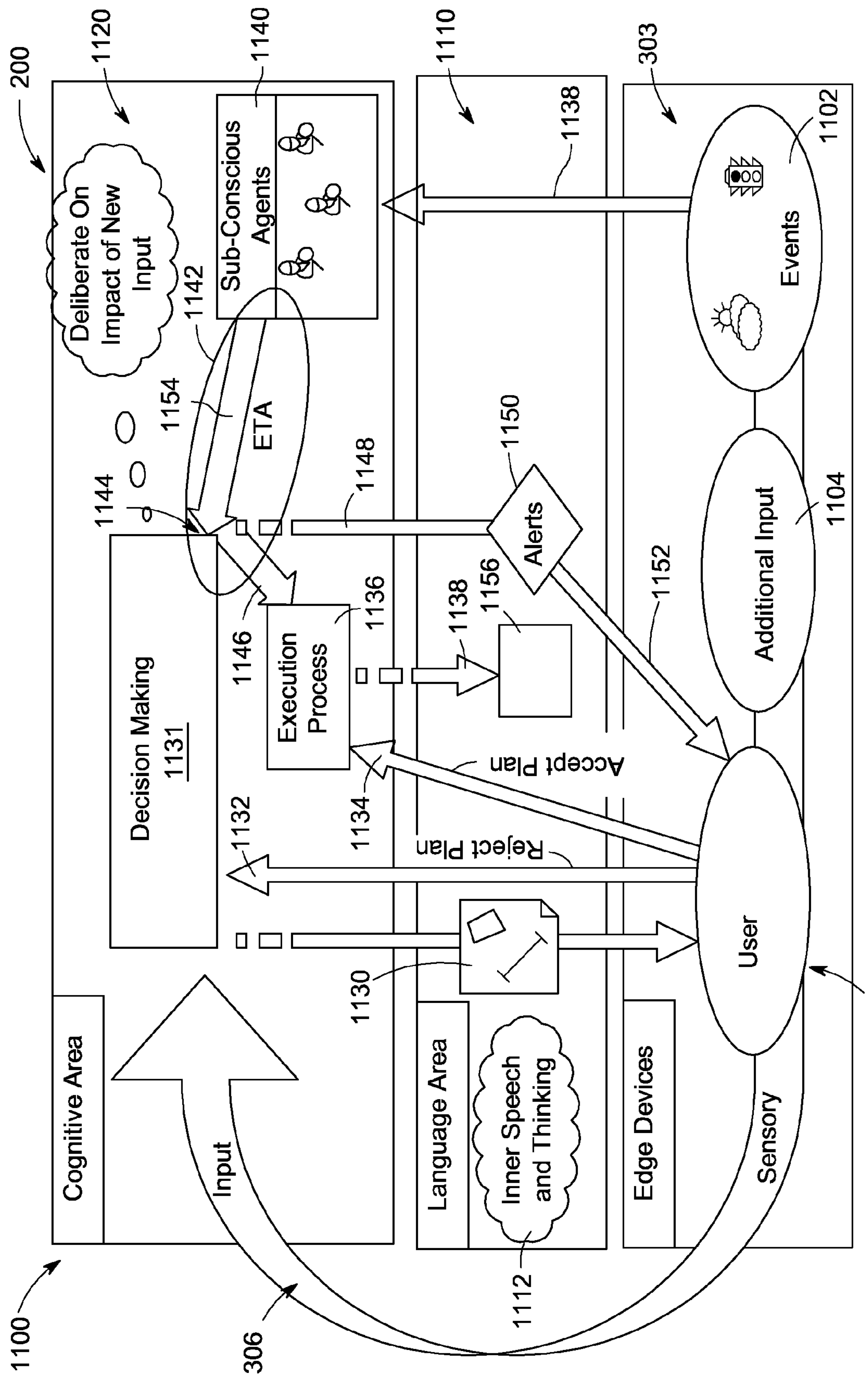
200
1120
1140
1110
303
1138
1102
Deliberate On Impact of New Input
Sub-Conscious Agents
Events
1142
1154
ETA
1150
1148
1144
Alerts
1104
Additional Input
1152
1136
1156
1138
1146
Execution Process
Decision Making
1131
Accept Plan
1132
1134
Reject Plan
User
1130
130
Cognitive Area
Language Area
Inner Speech and Thinking
Edge Devices
Sensory
Input
1112
1100
306

FIG. 18

COMPUTER-IMPLEMENTED SYSTEM WITH ADAPTIVE COGNITIVE FEATURES AND METHOD OF USING THE SAME

BACKGROUND OF THE INVENTION

The field of the invention relates generally to computer-implemented programs and, more particularly, to a computer-implemented system with adaptive cognitive learning features.

Most known supply chains include a system of organizations, people, and technology that initiate and manage activities, manage the flow of information and resources that manufacture, assemble, and distribute products and materials. Such organizations and people include suppliers, manufacturers, distributors, wholesalers, retailers, and consumers. The supply chains also facilitate relationships between the organizations and people.

At least some known computer-implemented supply chain management systems include sufficient programming to execute supply chain operation based on static data. For example, such systems can determine a least cost method of transporting a product between two points based upon statically-established fuel costs, labor costs, and shipping periods. However, such systems have limited resources for processing the large amounts of data, both static and dynamic data, as well as time sensitive data, typically associated with large-scale, international supply chain networks. Such data includes aging weather forecasts and traffic conditions. Also, such systems lack mechanisms to distinguish between valid data and invalid data.

Many such known systems require routine human intervention to input emergent data and to correct for unforeseen events. For example, human dispatchers facilitate enhancing the efficiency of a fleet by taking into account static variables such as delivery windows, contracted levels of service, and estimated times of arrival (ETA). In addition to these static variables, dispatchers also respond to dynamic conditions, for example, seasonal traffic conditions, unanticipated disruptive weather, and real-time driver behavior. For emergent adverse conditions, the dispatchers react to reduce the impact of those adverse conditions on operation after some period of latency associated with data collection, report delivery, and human deliberation. Furthermore, such systems require humans to perform pre-delivery planning and post-delivery analysis, wherein the post-delivery analysis is used as a feedback mechanism for subsequent pre-delivery planning. Moreover, since such systems lack adaptive cognitive features, including adaptive learning features, subsequent corrections for real-world, real-time, unanticipated events need to be directed by a human agent.

BRIEF SUMMARY OF THE INVENTION

In one aspect, a computer-implemented system is provided. The system includes an edge module and at least one input device coupled to the edge module. The at least one input device is configured to generate data input signals. The system also includes a cognitive module coupled to the edge module. The cognitive module includes a perception sub-module coupled to the edge module. The perception sub-module is configured to receive the data input signals. The cognitive module also includes a learning sub-module coupled to the perception sub-module. The learning sub-module is configured to adaptively learn at least in part utilizing the data input signals.

In a further aspect, a method of using a computer-implemented system having adaptable cognitive features is provided. The method includes executing instructions stored on a computer-readable medium. The instructions include generating a plurality of potential solutions in accordance with at least one predetermined goal of the computer-implemented system to ameliorate a dynamically determined condition based on at least one of real-time data inputs transmitted from at least one data input entity and at least one model formed and stored within the computer-implemented system. The instructions also include generating at least one scenario for each of the plurality of solutions defining at least one string of forecasted real world events resulting from implementation of each of the plurality of solutions. The forecasted real world events are at least one of possible and probable. The instructions further include comparing the strings of possible and probable forecasted real world events resulting from the implementation of each of the plurality of potential solutions to each other. The instructions also include selecting at least one course of action from the plurality of potential solutions based at least in part on the comparison. The instructions further include transmitting at least one directive associated with the at least one course of action to at least one operative entity, thereby executing the at least one course of action.

In another aspect, a method of using a computer-implemented system with adaptable cognitive features is provided. The method includes executing instructions stored on a computer-readable medium. The instructions include determining a pattern of performance of the computer-implemented system by analyzing at least one of historical data and previously generated courses of action. The instructions also include transmitting the pattern of performance to an adaptive cognitive module of the computer-implemented system. The instructions further include modifying a model using the adaptive cognitive module.

BRIEF DESCRIPTION OF THE DRAWINGS

These and other features, aspects, and advantages will become better understood when the following detailed description is read with reference to the accompanying drawings in which like characters represent like parts throughout the drawings, wherein:

FIG. **1** is a block diagram of an exemplary computing device that may be used to provide residence to at least a portion of an intelligent, neuromorphic, and adaptive cognitive system;

FIG. **2** is block diagram of a portion of an exemplary intelligent, neuromorphic, and adaptive cognitive system;

FIG. **3** is a schematic view of an exemplary high-level cognitive architecture that may be used with the adaptive cognitive system shown in FIG. **2**;

FIG. **4** is a flow chart of an exemplary model of perception data flow that may be used with the adaptive cognitive system shown in FIG. **2**;

FIG. **5** is a flow chart of an exemplary model of comparison data flow that may be used with the adaptive cognitive system shown in FIG. **2**;

FIG. **6** is a flow chart of an exemplary functional logic architecture that may be used with the adaptive cognitive system shown in FIG. **2**;

FIG. **7** is a view of the functional logic architecture shown in FIG. **6** in relationship to the high-level cognitive architecture shown in FIG. **3**;

FIG. **8** is a schematic view of an exemplary learning subsystem architecture that may be used with the functional logic architecture shown in FIG. **6** in relationship to the high-level cognitive architecture shown in FIG. **3**;

FIG. **9** is a schematic view of an exemplary problem solving subsystem architecture that may be used with the functional logic architecture shown in FIG. **6** in relationship to the high-level cognitive architecture shown in FIG. **3**;

FIG. **10** is a flow chart of an exemplary input and output (I/O) architecture that may be used with the functional logic architecture shown in FIGS. **6** and **7**;

FIG. **11** is a flow chart of an exemplary implementation of a learning controller sequence that may be used with the I/O architecture shown in FIG. **10**;

FIG. **12** is a flow chart of an exemplary support vector machine (SVM) clustering portion of the learning controller sequence shown in FIG. **11**;

FIG. **13** is a flow chart of an exemplary artificial neural network (ANN) and genetic algorithm (GA) portion of the learning controller sequence shown in FIG. **11**;

FIG. **14** is a flow chart of an exemplary SVM learning portion of the learning controller sequence shown in FIG. **11**;

FIG. **15** is a flow chart of an exemplary model of generalized continuous learning that may be used with the adaptive cognitive system shown in FIG. **2**;

FIG. **16** is a flow chart of an exemplary model of learning during execution of a plan, and adapting to changes in the plan, wherein the plan includes multiple shipping routes and trips, such model may be used with the adaptive cognitive system shown in FIG. **2**;

FIG. **17** is a flow chart of an exemplary model of problem solving during derivation of an estimated time of arrival for a route and trip that may be used with the adaptive cognitive system shown in FIG. **2**; and

FIG. **18** is a flow chart of an exemplary model of a decision making process that may be used with the adaptive cognitive system shown in FIG. **2**.

Unless otherwise indicated, the drawings provided herein are meant to illustrate key inventive features of the invention. These key inventive features are believed to be applicable in a wide variety of systems comprising one or more embodiments of the invention. As such, the drawings are not meant to include all conventional features known by those of ordinary skill in the art to be required for the practice of the invention.

DETAILED DESCRIPTION OF THE INVENTION

In the following specification and the claims, reference will be made to a number of terms, which shall be defined to have the following meanings.

The singular forms "a", "an", and "the" include plural references unless the context clearly dictates otherwise.

"Optional" or "optionally" means that the subsequently described event or circumstance may or may not occur, and that the description includes instances where the event occurs and instances where it does not.

As used herein, the terms "intelligence" and "intelligent" are intended to be descriptive of any computer-implemented programs and computer-based systems that are implemented such that they demonstrably exhibit abilities, including, without limitation, attention, abstract thought, understanding, communication, reasoning, learning, planning, emotional intelligence and/or problem solving.

As used herein, the terms "neuromorphic programs" and "neuromorphic systems" are intended to be representative of any computer-implemented programs and computer-based systems that are implemented such that they emulate neurobiological architectures present in the nervous system. Also, as used herein, the terms "neuromorphic programs" and "neuromorphic systems" are intended to be representative of any combination of analog, digital, mixed-mode analog/digital, and software systems that implement models of neural systems that emulate, without limitation, human perception, human motor control, and human sensory processing. Further, as used herein, such neuromorphic programs and systems are flexible and may morph and/or adapt to emergent conditions as necessary.

As used herein, the terms "cognitive" and "cognition" are intended to be descriptive of any computer-implemented programs and computer-based systems that execute processes that include, without limitation, continuous learning, adaptation, planning, remembering, forgetting, language, memory structure, perception, communicating, deliberating, applying knowledge, solving problems, making decisions, changing preferences, sensory input, internal thinking, and reflex actions. Cognition, or cognitive processes, can be artificial including states of intelligent entities, such as, highly autonomous machines and artificial intelligences that have the ability to process, e.g., take into consideration, feedback from the environment.

As used herein, the term "asset management system" is intended to be representative of any computer-implemented programs and computer-based systems that facilitate, without limitation, design, planning, execution, control, and monitoring of assets. Such asset management systems include, without limitation, "supply chain management (SCM) systems." As used herein, SCM systems facilitate executing activities that include, without limitation, tracking movement and storage of raw materials, tracking work-in-process inventory, and tracking finished goods from a point of origin to a point of consumption, and synchronizing supply with demand.

As used herein, the terms "intelligent system", "artificial intelligence", "intelligent agent", and "artificial consciousness" are intended to be representative of, without limitation, any computer-implemented programs and computer-based systems that perceive their environments, independently determine courses of action, and take the actions that will maximize the chances of success.

As used herein, the terms "artificial neural network (ANN)" and "neural network (NN)" are intended to be representative of any computer-implemented programs and computer-based systems that model complex relationships between inputs and outputs or to find patterns in data. Also, as used herein, ANNs and NNs are adaptive systems that change their structure based on external or internal information that flows through the network during a learning phase.

As used herein, the term "support vector machine (SVM)" is intended to be representative of any computer-implemented and computer-based classification methods that construct hyperplanes in multidimensional space to analyze data, recognize patterns, classify and sort such data with similar attributes into one set of defined groups, categorize and sort such data with similar and/or differing attributes into other sets of defined groups, and develop the ability to predict such classification and/or categorization after "training" with training data.

As used herein, the term "SVM clustering" is intended to be representative of any computer-implemented and computer-based methods that use an SVM-based clustering algorithm to classify and categorize data according to the attributes of the data. Such attributes may be predefined, including each attribute having a predefined relevance, and the clustering algorithm will cluster according to the predefined attributes and their degree of relevance. Such SVM clustering algorithms are typically referred to as "supervised" SVM algorithms and require external support for their training. Alternatively, such attributes may be undefined and the clustering algorithm will self-determine such attributes, sort accordingly, and review the sorted data for attribute consistency, thereby performing self-training. Such SVM clustering algorithms are typically referred to as "non-parametric" SVM algorithms and require little to no external support for their training.

As used herein, the term "sparse distributed memory (SDM)" is intended to be representative of any computer-implemented and computer-based random-access, content addressable memory that mathematically model human long-term memory for storing and retrieving large amounts (i.e., in excess of 2^{1000} bits) of information without focusing on the accuracy of the information. Such sparse distributed memory uses patterns to serve as memory addresses, where information is retrieved based on similarities between addresses. Memory addresses are all in a list even if they are not related, but are only retrieved based on similar content between them. Also, as used herein, SDM can be used as a perceptual memory system that allows for retrieving best-match memories, associative memories, sequences, and predicting future inputs.

As used herein, the term "genetic algorithm (GA)" is intended to be representative of any portion of computer-implemented programs and computer-based systems that includes a search heuristic that emulates the process of natural evolution to generate useful solutions to optimization and search problems.

As used herein, the term "heuristic" is intended to be representative of any portion of computer-implemented programs and computer-based systems that uses experience-based techniques for problem solving, learning, and discovery.

As used herein, the term "Java® Native Interface (JNI, or Jini)" is intended to be representative of any computer-implemented programs and computer-based systems that are a programming framework that enables Java® code running in a Java® Virtual Machine (JVM) to call, and to be called by, native applications, i.e., programs specific to a hardware and operating system platform, and libraries written in other languages, e.g., C, C++, and assembly. Java® is a registered trademark of Oracle Corporation headquartered in Redwood Shores, Calif., USA.

As used herein, the term "thread" is intended to be representative of the smallest unit of any computer-implemented and computer-based processing that can be scheduled by an operating system.

As used herein, the term "model-view-controller (MVC)" is intended to be representative of any computer-implemented and computer-based software architectural pattern that isolates "domain logic", i.e., the application logic for the user, from the user interface (UI), i.e., input and presentation, thereby facilitating independent development, testing and maintenance of each, while facilitating a loose coupling between these elements.

As used herein, the term "non-transitory computer-readable media" is intended to be representative of any tangible computer-based device implemented in any method or technology for short-term and long-term storage of information, such as, computer-readable instructions, data structures, program modules and sub-modules, or other data in any device. Therefore, the methods described herein may be encoded as executable instructions embodied in a tangible, non-transitory, computer readable medium, including, without limitation, a storage device and/or a memory device. Such instructions, when executed by a processor, cause the processor to perform at least a portion of the methods described herein.

Moreover, as used herein, the term "non-transitory computer-readable media" includes all tangible, computer-readable media, including, without limitation, non-transitory computer storage devices, including, without limitation, volatile and nonvolatile media, and removable and non-removable media such as a firmware, physical and virtual storage, CD-ROMs, DVDs, and any other digital source such as a network or the Internet, as well as yet to be developed digital means, with the sole exception being a transitory, propagating signal.

As used herein, the term "dynamic contextual data" is intended to be representative of any data that includes contextual associations and interrelationships with respect to any other data in a dynamic environment. Similarly, as used herein, "static contextual data" is intended to be representative of any data that includes contextual associations and interrelationships with respect to any other data in a static environment.

As used herein, the terms "software" and "firmware" are interchangeable, and include any computer program stored in memory for execution by devices that include, without limitation, mobile devices, clusters, personal computers, workstations, clients, and servers.

As used herein, the term "real-time" refers to at least one of the time of occurrence of the associated events, the time of measurement and collection of predetermined data, the time to process the data, and the time of a system response to the events and the environment. In the embodiments described herein, these activities and events occur substantially instantaneously.

As used herein, the term "computer" and related terms, e.g., "computing device", are not limited to integrated circuits referred to in the art as a computer, but broadly refers to a microcontroller, a microcomputer, a programmable logic controller (PLC), an application specific integrated circuit, and other programmable circuits, and these terms are used interchangeably herein.

Approximating language, as used herein throughout the specification and claims, may be applied to modify any quantitative representation that could permissibly vary without resulting in a change in the basic function to which it is related. Accordingly, a value modified by a term or terms, such as "about" and "substantially", are not to be limited to the precise value specified. In at least some instances, the approximating language may correspond to the precision of an instrument for measuring the value. Here and throughout the specification and claims, range limitations may be combined and/or interchanged, such ranges are identified and include all the sub-ranges contained therein unless context or language indicates otherwise.

FIG. **1** is a block diagram of an exemplary computing device **105** that may be used to provide residence to at least a portion of an intelligent, neuromorphic, cognitive, computer-implemented asset management system with adaptive cognitive features, i.e., an intelligent, neuromorphic, cognitive asset management, or supply chain management (SCM) system (not shown in FIG. **1**).

Computing device **105** includes a memory device **110** and a processor **115** operatively coupled to memory device **110** for executing instructions. Processor **115** may include one or more processing units (e.g., in a multi-core configuration). In some embodiments, executable instructions are stored in memory device **110**. Computing device **105** is configurable to perform one or more operations described herein by programming processor **115**. For example, processor **115** may be programmed by encoding an operation as one or more executable instructions and providing the executable instructions in memory device **110**.

In the exemplary embodiment, memory device **110** is one or more devices that enable storage and retrieval of information such as executable instructions and/or other data. Memory device **110** may include one or more tangible, non-transitory computer-readable media, such as, without limitation, random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), a solid state disk, a hard disk, read-only memory (ROM), erasable programmable ROM (EPROM), electrically erasable programmable ROM (EEPROM), and/or non-volatile RAM (NVRAM) memory. The above memory types are exemplary only, and are thus not limiting as to the types of memory usable for storage of a computer program.

Also, in the exemplary embodiment, memory device **110** includes a sparse distributed memory (SDM) configuration, wherein such SDM configuration is defined using software. Alternatively, such SDM configuration is defined using any combination of SDM-capable hardware and SDM-compatible software that enables operation of the adaptive cognitive system as described herein.

Memory device **110** may be configured to store operational measurements including, without limitation, shipping points, destination points, real-time weather and traffic conditions therebetween, and/or any other type of data. In some embodiments, processor **115** removes or "purges" data from memory device **110** based on the age of the data. For example, processor **115** may overwrite previously recorded and stored data associated with a subsequent time and/or event. In addition, or alternatively, processor **115** may remove data that exceeds a predetermined time interval. Also, memory device **110** includes, without limitation, sufficient data, algorithms, and commands to facilitate operation of the intelligent, neuromorphic, cognitive system with adaptive cognitive features (discussed further below).

In some embodiments, computing device **105** includes a presentation interface **120** coupled to processor **115**. Presentation interface **120** presents information, such as a user interface and/or an alarm, to a user **125**. In one embodiment, presentation interface **120** includes a display adapter (not shown) that is coupled to a display device (not shown), such as a cathode ray tube (CRT), a liquid crystal display (LCD), an organic LED (OLED) display, and/or an "electronic ink" display. In some embodiments, presentation interface **120** includes one or more display devices. In addition, or alternatively, presentation interface **120** includes an audio output device (not shown) (e.g., an audio adapter and/or a speaker) and/or a printer (not shown). In some embodiments, presentation interface **120** presents an alarm associated with a synchronous machine (not shown in FIG. **1**), such as by using a human machine interface (HMI) (not shown).

In some embodiments, computing device **105** includes a user input interface **130**. In the exemplary embodiment, user input interface **130** is coupled to processor **115** and receives input from user **125**. User input interface **130** may include, for example, a keyboard, a pointing device, a mouse, a stylus, a touch sensitive panel (e.g., a touch pad or a touch screen), and/or an audio input interface (e.g., including a microphone). A single component, such as a touch screen, may function as both a display device of presentation interface **120** and user input interface **130**.

A communication interface **135** is coupled to processor **115** and is configured to be coupled in communication with one or more other devices, such as a sensor or another computing device **105**, and to perform input and output operations with respect to such devices. For example, communication interface **135** may include, without limitation, a wired network adapter, a wireless network adapter, a mobile telecommunications adapter, a serial communication adapter, and/or a parallel communication adapter. Communication interface **135** may receive data from and/or transmit data to one or more remote devices. For example, a communication interface **135** of one computing device **105** may transmit an alarm to the communication interface **135** of another computing device **105**. Communications interface **135** facilitates machine-to-machine communications, i.e., acts as a machine-to-machine interface.

Presentation interface **120** and/or communication interface **135** are both capable of providing information suitable for use with the methods described herein (e.g., to user **125** or another device). Accordingly, presentation interface **120** and communication interface **135** may be referred to as output devices. Similarly, user input interface **130** and communication interface **135** are capable of receiving information suitable for use with the methods described herein and may be referred to as input devices. Interaction of the intelligent, neuromorphic, cognitive systems described herein with a human are not limited to presentation interface **120** and communication interface **135**. Rather, other devices (none shown) may be used to communicate with the intelligent, neuromorphic, cognitive systems, for example, without limitation, portable devices with a man-machine-interface (MMI).

FIG. **2** is block diagram of a portion of an exemplary intelligent, neuromorphic, cognitive system **200** with adaptive features, i.e., an exemplary adaptive cognitive system **200**. System **200** includes at least one computing device **105** that is coupled to other devices **220** via a communication network **225**. Embodiments of network **225** may include operative coupling with, without limitation, the Internet, a local area network (LAN), a wide area network (WAN), a wireless LAN (WLAN), and/or a virtual private network (VPN). While certain operations are described below with respect to particular computing devices **105**, it is contemplated that any computing device **105** may perform one or more of the described operations.

Referring to FIGS. **1** and **2**, in the exemplary embodiment, computing device **105** is coupled to network **225** via communication interface **135**. In an alternative embodiment, computing device **105** is integrated with other devices **220**. Computing device **105** interacts with a first operator **230** (e.g., via user input interface **130** and/or presentation interface **120**). In one embodiment, computing device **105** presents information about system **200**, such as alarms, to operator **230**. Other devices **220** interact with a second operator **235** (e.g., via user input interface **130** and/or presentation interface **120**). For example, other devices **220** present alarms and/or other operational information to second operator **235**. As used herein, the term "operator" includes any person or machine in any capacity associated with operating and maintaining system **200**, including, without limitation, warehouse operations personnel, system maintenance technicians, system supervisors, and interfacing external systems similar to system **200** and/or automated monitoring systems and operating systems.

In the exemplary embodiment, adaptive cognitive system **200** includes one or more monitoring sensors **240**. Monitoring sensors **240** collect operational data including, without limitation, real-time shipment and delivery information, real-time warehouse inventory information, real-time status information from warehouse robots, real-time weather and traffic information, and/or any other type of data. Such data and information may be obtained from devices that include, without limitation, gyroscopes, accelerometers, position detectors, global positioning systems (GPSs), and Internet resources. Monitoring sensors **240** repeatedly (e.g., periodically, continuously, and/or upon request) transmit operational data at the time of measurement and/or receipt. Computing devices **105** within system **200** receive and process the operational data. Also, each computing device **105** includes, without limitation, sufficient data, algorithms, and commands to facilitate centralized and/or distributed monitoring and management of system **200** (discussed further below).

FIG. **3** is a schematic view of an exemplary high-level cognitive architecture **300** that may be used with adaptive cognitive system **200**. System **200** is versatile and scalable and is not limited to any one practical application. Rather, system **200** can be used to facilitate any process that benefits from control and monitoring through an application that continuously learns, adapts, and determines modifications to execution plans as a result of real-time information. System **200** may be used as any stand-alone system including, without limitation, asset management systems, supply chain management systems, and warehouse management systems. Also, system **200** may be implemented within any facility requiring cognitive systems with real-time adaptive features, such facilities including, without limitation, electric power generation facilities, electric power transmission and distribution networks, chemical processing facilities (e.g., refineries), fabrication and assembly facilities, bottling and packaging facilities, patient care networks, and communications networks.

System **200** includes an edge module **302** that includes a plurality of edge devices **303** that facilitate coupling of system **200** to the real world **304**. Edge devices **303** include, without limitation, sufficient input and output devices of any type that enable operation of system **200** as described herein.

Edge module **302** includes a sensory input sub-module **306** configured to receive inputs from at least one input entity (not shown in FIG. **3**). In the exemplary embodiment, real world **304** includes a plurality of input entities, wherein at least some of the input entities are any devices that interface with real world **304** to measure and/or record conditions in real world **304**, such as monitoring sensors **240** (shown in FIG. **2**), including, without limitation, devices that measure and transmit temperatures, remaining power storage of mobile warehouse robots, lubrication levels of articulated joints of factory robots, and conveyor belts' alignment. The plurality of input entities also includes other devices **220** (shown in FIG. **2**), such as other interfacing systems and agents, including, without limitation, weather forecasting systems, global positioning system (GPS) satellite management systems, facility security systems, enterprise resource planning (ERP) systems, and control systems for communication network **225** (shown in FIG. **2**). Moreover, the plurality of input entities includes computing device **105** (shown in FIGS. **1** and **2**). Furthermore, the plurality of input entities includes, without limitation, user **125** (shown in FIG. **1**) and operators **230** and **235** (both shown in FIG. **2**). Also, the plurality of input entities includes sources of information derived internally within system **200**, including, without limitation, directions and actions generated by system **200**. Sensory input sub-module **306** transmits outputs **307** representative of the inputs received.

In the context of asset management, examples of additional data that may be transmitted from real world **304** include, without limitation, maps of shipping routes, available and unavailable roads, regional traffic and weather conditions, regional crime statistics, regional time of day, and season of the year. Also, in the context of asset management, examples of additional data that may be self-transmitted from resources internal to system **200** include, without limitation, available trailers, trailer conditions, available robots, warehouse inventories (including, wrongly placed inventory), cargo status,

vehicle GPS-generated location data, and cargo temperatures. Further, in the context of asset management, examples of additional data that may be input by a human, i.e., user **125**, or a human and/or machine, i.e., operators **230** and **235**, in the roles of shipping planner and shipping receiver includes, without limitation, matching cargo with destinations, selecting arrival times, cargo conditions, potential events that initiate an alert based on a priority of the shipment, allowable variations in arrival times, and locations to avoid during transit.

At the sensory input level, there is some filtering and preprocessing of the incoming information. For example, the inputs may be monitored consciously by system **200** through a direct information request. More specifically, environmental conditions of a region may be monitored against known and expected conditions for such region and a mismatch may be flagged for further investigation. Also, the inputs may be monitored subconsciously through associated agents looking for specific information and drawing the attention of system **200** to new important changes in the environment, for example, without limitation, those instances where online changes to weather and traffic data are implemented.

Also, in the exemplary embodiment, edge module **302** includes a reflex sub-module **308** coupled to sensory input sub-module **306**. Reflex sub-module **308** is configured to generate at least one autonomic response **309** to outputs **307** transmitted from the plurality of input entities, thereby bypassing cognitive portions of system **200** (discussed further below). Reflex sub-module **308** facilitates at least a portion of intelligent and neuromorphic operation of system **200** as described herein. Such autonomic responses **309** may be automatically delegated to reflex sub-module as system **200** learns. As system **200** determines that certain conditions do not need to be transmitted through the cognitive portions of system **200**, system resolution and/or management of such certain conditions is "pushed-down" to reflex sub-module **308**, thereby reducing the use of dedicated cognitive resources for relatively simple conditions and issues.

In the context of asset management, examples of conditions that can be easily resolved through reflex sub-module **308** include inputs from a shipping planner that are outside established parameters and/or are not logical. Examples of such planner inputs include, without limitation, a blizzard in Arizona and delivery of goods shipped from Los Angeles, USA to Chicago, USA in one hour. Also, in the context of asset management, examples of conditions that can be easily resolved through reflex sub-module **308** include, without limitation, adjusting a warehouse thermostat setting to resolve temperatures outside of established thresholds, and sending alerts for low tire pressures and open doors on vehicles. Further, in the context of asset management, examples of conditions that can be easily resolved through reflex sub-module **308** include, without limitation, directing warehouse robots to avoid obstacles and to send an alert when an item leaves a warehouse without an authorized shipping notice.

Further, in the exemplary embodiment, edge devices **302** include an action sub-module **310** coupled to reflex sub-module **308**. Action sub-module **310** is configured to receive autonomic responses **309** transmitted from reflex sub-module **308**. Action sub-module **310** is also configured to transmit directives **311** through output devices (not shown in FIG. **3**) resident within edge module **302** to operative entities (not shown in FIG. **3**) in real world **304**. Directives **311** direct execution of a predetermined course of action in real world **304** as a function of autonomic responses **309**. As such, action sub-module **310** initiates, facilitates, and directs physical and tangible effects **312** in real world **304** through transmission of directives **311** to the operative entities.

Edge module **302** receives feedback **314** induced by effects **312** as induced by directives **311** as they are transmitted by action sub-module **310** to the operative entities in real world **304**. Also, sensory input sub-module **306** receives feedforward information **316** at least partially induced by directives **311** transmitted by action sub-module **310**, thereby alerting sensory input sub-module **306** to anticipate certain feedback **314**. At least some of the data **324** received by sensory input sub-module **306** includes static and dynamic contextual data **318** and feedback **314**, both transmitted from sources in real world **304**. Examples of static and dynamic contextual data **318** include, without limitation, statically stored historical weather and traffic data and dynamic real-time weather and traffic data, respectively.

System **200** also includes an adaptive cognitive module **320** that performs a significant portion of intelligent, neuromorphic, and cognitive operation of system **200** as described herein. Cognitive module **320** includes a perception sub-module **322** coupled to sensory input sub-module **306**. Perception sub-module **322** is configured to receive static and dynamic contextual data **318** in addition to other predetermined data **324** from sensory input sub-module **306** and the associated input entities. Perception sub-module **322** is also configured to augment incoming data **324**, including static and dynamic contextual data **318** depending on the attention, experience, context, and expectations of system **200** as discussed further below. Perception sub-module **322** is further configured to preprocess incoming information by analyzing incoming data **324** and interpreting the information in data **324** to determine the subsequent use of the data **324**. In making such determinations, perception sub-module **322** uses conscious goals of system **200**, subconscious goals of system **200**, and/or external agent-based behavior, as discussed further below. Perception sub-module **322** is further configured to perceive an episodic sense of time through system **200**'s perception of events and stored memories of such events. Therefore, system **200** demonstrates the ability to estimate long and short time intervals and perceive time emotionally, i.e., perceiving the speed of time as passing slowly when waiting for an event to occur in contrast to time passing more quickly when satisfactory, or pleasing events are occurring.

Adaptive cognitive module **320** also includes an emotion sub-module **330** configured to distinguish between positive outcomes and negative outcomes, i.e., emotion sub-module **330** generates an emotional response to real world effects **312** generated as a result of executing course of action **384**. Therefore, system **200** makes determinations of events and data that are good, bad, pleasant, and unpleasant, and modifies course of action **384** accordingly. For example, without limitation, incoming data **324** is compared with expected values and can change perceptions generated by perception sub-module **322** to trigger an emotional response to static and dynamic contextual data **318** and real world effects **312**.

Adaptive cognitive module **320** further includes a comparison sub-module **332** that is coupled to perception sub-module **322** and emotion sub-module **330**. Comparison sub-module **332** is configured to compare at least a portion **334** of incoming data **324** with predetermined, expected values stored within system **200** and make a determination if the comparison is a positive or a negative result. Therefore, emotion sub-module **330** influences comparison sub-module **332**, for example, without limitation, events and data that are perceived by system **200** to be good, bad, pleasant, and unpleasant, will be compared according to such perceptions.

Adaptive cognitive module **320** also includes a memory sub-module **336** that is coupled to perception sub-module **322**, emotion sub-module **330**, and comparison sub-module **332**. Memory sub-module **336** is configured to store at least a portion **338** of incoming data **324** for further use within system **200**. Memory sub-module **336** includes a plurality of memory devices **110**, and is therefore physically and virtually distributed throughout system **200**. Memory sub-module **336** is configured to store a plurality of data and data types therein, including, without limitation, processed data, historical data, user and customer preferences, user and customer alerts and alarms, data models, learned patterns, previously compared data, and algorithms. Emotion sub-module **330** influences memory sub-module **336**, for example, without limitation, events and data that are perceived by system **200** to be good, bad, pleasant, and unpleasant, will be stored in memory according to such perceptions.

As described above, memory sub-module **336** is a software-configured SDM that substantially models human memory to facilitate learning, pattern recognition, and self-guided decision capabilities. It can be used as a perceptual memory system that allows for retrieving best-match memories, associative memories, sequences, and predicting future inputs. SDM creates a multi-dimensional address space, and populates that address space with hard locations, i.e., physical places where data can actually be stored. When storing information, a defined sphere of activation distributes the data among several of the hard locations, thereby creating redundancy and creating an archetype memory that can later be retrieved with only partial cues. Information is retrieved through a series of converging recalls that point to an archetypical data storage location. Such archetypical data storage is described further below and facilitates long-term memory storage of data and models, fuzzy retrieval, partial matching, and determining connections between data and models.

Such SDM stores raw data and processed data, including, without limitation, patterns, algorithms, and models. In the context of an asset management implementation, such data includes, without limitation, past weather, geographic regions, user preferences, trailer availability, upper and lower specification limits for temperatures, assets and their locations, roads, maps, time, past decisions, alerts, customer business rules, lists of possible actions, and events (temporally organized). In general, SDM facilitates storage of data models, learned performances, event patterns, previously compared results, and associated algorithms.

As described above, memory sub-module **336** is physically and virtually distributed throughout system **200** while being embedded, and distributed, within cognitive module **320**. A first portion (not shown) of memory sub-module **336** is dedicated to short-term, working memory. In the context of an asset management implementation, working memory may be used to hold data such as, without limitation, data associated with cargo shipment trips and loads currently being processed. A second portion (not shown) of memory sub-module **336** is dedicated to procedural and working memory, wherein such working memory facilitates construction of events with a temporal character, i.e., the abilities of system **200** to sense time and to form episodic memories of events in a series of temporally-organized data. In the context of an asset management implementation, such working memory facilitates, without limitation, construction of future trips and reconstruction of previously completed trips.

A third portion (not shown) of memory sub-module **336** includes semantic long-term memory, i.e., memory in which associations among items are stored as part of a dual-store memory model, in contrast to a single-store retrieved context model including only working memory. Alternatively, the third portion of memory sub-module **336** includes "Knowledge-line", typically shortened to K-line memories, i.e., a mental agent associated with a group of other mental agents that are called, or recalled, after a certain problem is solved or a new idea is formulated. In the context of an asset management implementation, such long-term memory facilitates, without limitation, rapid recall of frequently requested trips and routes, seasonal and conditional associations with routes, and user preferences.

Adaptive cognitive module **320** further includes an adaptive on-line learning sub-module **340** that is coupled to perception sub-module **322**, emotional sub-module **330**, comparison sub-module **332**, and memory sub-module **336**. Learning sub-module **340** is configured to receive at least a portion **342** of incoming data **324**. Learning sub-module **340** includes, without limitation, a plurality of implemented learning algorithms (discussed further below) that facilitates adaptive cognitive system **200** being generally adaptable to a variety of emergent problems that may arise during operation of system **200**. From a broad perspective, adaptive on-line learning sub-module **340** facilitates system **200** acquiring a wide range of background knowledge based on interaction with real world **304**.

Adaptive on-line learning sub-module **340** is configured to adaptively learn as a function of static and dynamic contextual data **318** received while system **200** is on-line, i.e., operatively coupled to, and interacting with, real world **304** through edge module **302**. Learning sub-module **340** is also configured to generate a plurality of data clusters, wherein each of the data clusters is defined as a function of at least one attribute. Learning sub-module **340** is further configured to form at least one model from at least a portion of the data clusters, wherein the models are configured to substantially represent actual processes and physical artifacts in real world **304**. As discussed further below, learning sub-module **340** is configured to learn from past experiences through feedback **314** and modify at least one of the models based on feedback **314**, as well as historical data, contextual data, and other on-line data thereby defining at least one modified model. In this respect, emotion sub-module **330** influences learning sub-module **340**, for example, without limitation, events and data that are perceived by system **200** to be good, bad, pleasant, and unpleasant, will be influence learning by system **200** according to such perceptions.

In the exemplary embodiment, adaptive cognitive module **320** also includes a data highway **344** that couples adaptive on-line learning sub-module **340**, comparison sub-module **332**, and memory sub-module **336** to each other. Data highway **344** defines a physical and virtual structure that couples distributed resources and devices.

Cognitive module **320** further includes a problem solving sub-module **350** coupled to perception sub-module **322**, comparison sub-module **332**, memory sub-module **336**, and learning sub-module **340**. Problem solving sub-module **350** is configured to receive at least a portion **352** of incoming data **324** from perception sub-module **322**, including static and dynamic contextual data **318**. Problem solving sub-module **350** includes a plurality of implemented planning/decisioning algorithms (discussed further below) that facilitates adaptive cognitive system **200** being generally adaptable to a variety of emergent problems that may arise during operation of system **200**.

Problem solving sub-module **350** is configured to generate at least one potential solution **353** in accordance with at least one predetermined goal of adaptive cognitive system **200** to ameliorate a condition based on at least one of static and

dynamic contextual data **318** transmitted from perception sub-module **322** and at least one model defined within memory sub-module **336** and learning sub-module **340**. Problem solving sub-module **350** is further configured to generate a new solution and modify an existing solution as a function of the modified models. Problem solving sub-module **350** is coupled to comparison sub-module **332**, memory sub-module **336**, and learning sub-module **340** through two-way communication channels **354**.

Adaptive cognitive module **320** also includes an internal thinking sub-module **360** that is coupled to problem solving sub-module **350**. In the exemplary embodiment, at least a portion of internal thinking sub-module **360** is embedded within problem solving sub-module **350** and at least a portion of internal thinking sub-module **360** is external to, and coupled to, problem solving sub-module **350**. Alternatively, internal thinking sub-module **360** is either fully embedded within, or fully external to, problem solving sub-module **350**. Internal thinking sub-module **360** is configured to generate at least one scenario **362** defining at least one string of forecasted real world events resulting from implementation of a course of action selected from potential solutions **353**, wherein the forecasted real world events are at least one of possible and probable. Also, data **352** transmitted from perception sub-module **322** facilitates generating at least one scenario **362** by internal thinking sub-module **360**. Examples of real world events that may be included within scenario **362** include, without limitation, likely (and unlikely) weather patterns and traffic patterns.

Inherent within adaptive cognitive system **200** are communications features that couple the components of system **200** as described herein. For example, without limitation, real world data is transmitted to internal thinking sub-module **360**, wherein real world data includes at least some static and dynamic contextual data **318**. Also, such communication features include at least portions of communication interface **135** that facilitate communication between adaptive cognitive system **200** and other systems and devices to share knowledge and data therebetween. The language used for communications within, and external with, system **200** are selected by system **200** based on the current issues/problems being addressed by system **200**, such language including, without limitation, machine-to-machine language for knowledge sharing.

Cognitive module **320** also includes a deliberation sub-module **380** coupled to problem solving sub-module **350**, action sub-module **310**, and perception sub-module **322**. In the exemplary embodiment, deliberation sub-module **380** is configured to receive at least a portion **382** of incoming data **324** and compare potential solutions **353** transmitted from problem solving sub-module **350**. Deliberation sub-module **380** is also configured to select at least one course of action **384** from potential solutions **353**. Deliberation sub-module **380** is further configured to transmit such course of action **384** to action sub-module **310** such that action sub-module **310** generates and transmits directives **311** to operative entities (not shown in FIG. **3**) in real world **304** to execute course of action **384** in real world **304**. Deliberation sub-module **380** includes decision-making features that facilitate choosing course of action **384** from potential solutions **353**, wherein such decision-making features also facilitate selection of decisions in dynamic environments and in static environments using dynamic data and static data. Deliberation sub-module **380** uses information stored in memory sub-module **336**, including, without limitation, models, events, preprocessed sensory input, and the current emotional state of system **200**.

Courses of action **384** differ from autonomic responses **309** in that autonomic responses **309** are generated subconsciously, i.e., automatically in response to certain outputs **307** transmitted from sensory input sub-module **306**, thereby bypassing cognitive module **320**. Such autonomic responses **309** are similar to subconscious, impulsive actions performed by humans that require little to no deliberation, e.g., adjusting an angle and distance of reading materials to more easily read the words. In the context of asset management, examples of conditions that can be easily resolved through autonomic responses **309** include, without limitation, adjusting a warehouse thermostat setting to resolve temperatures outside of established thresholds, and directing warehouse robots to avoid obstacles.

In contrast, courses of action **384** are generated as a function of analysis and deliberation of incoming data **324** by system **200** on a conscious level, i.e. cognitive level. Such courses of action **384** are similar to deliberate, i.e., intentional decisions made by humans, e.g., selection of the reading materials. Adaptive cognitive system **200** thereby demonstrates intentionality based on cognitive deliberation. Courses of action **384** may be generated as a response to changes in the state of an edge device representative of a change in real world **304** or a virtual change. In the context of asset management, examples of conditions that can be resolved through deliberation and intentional action include, without limitation, redirecting a shipment based on emergent and adverse traffic conditions in the near vicinity of the shipment. One possible action is no action at all.

FIG. **4** is a flow chart of an exemplary model **386** of perception data flow that may be used with adaptive cognitive system **200** (shown in FIG. **2**). In the exemplary embodiment, perception sub-module **322** facilitates "making sense" the current situation based on incoming data **324** (shown in FIG. **3**) that includes feedback **314**.

In general, perception sub-module **322** facilitates interpreting hidden data in the raw sensory information and determines if the input data requires action in terms of problem solving, learning, or deliberation. Such data routing decisions in perception sub-module **322** are directed by conscious goals of system **200**, subconscious goals of system **200**, or agent-based behavior of system **200**. Operation of perception sub-module **322** is directly influenced by attention, expectations, context, and emotions. When conducting a task, system **200** may be focused on either a single item/issue or a plurality of items/issues. The degree of attention directed towards the incoming data and the associated conditions and situations directly affects the amount of cognitive resources that will be directed to such conditions and situations. Also, the degree of attention to any particular problem depends on factors that include, without limitation, the nature and magnitude of the problem and the goals to be achieved.

The expectations of system **200** will determine if the degree of attention should be increased, decreased, or kept as is based on the degree of success of directives **311** as shown through effects **312** (both shown in FIG. **3**). The context of the incoming data influences the degree of attention directed toward the incoming data, wherein data indicative of a primary effect will receive more attention than data associated with less critical effects. The emotions of system **200** are used to influence operation of perception sub-module **322**, wherein a positive result and a negative result will have different effects on system **200**.

Also, in general, with respect to perception sub-module **322** and system **200**, perception is more than mere pattern recognition, i.e., perception includes use of sensory information, embedded information in system **200**, e.g., the model of real world **304** (shown in FIG. **3**) and the self-contained model of system **200**.

In the exemplary embodiment, model **386** includes memory sub-module **336** coupled to sensory input sub-module **306** and perception sub-module **322** through at least a portion of feedback **314**. Model **386** also includes a preprocess function block **388** positioned between sensory input sub-module **306** and perception sub-module **322**. As described above, system **200** performs some filtering and preprocessing of the incoming information, wherein preprocess function block **388** performs the filtering and preprocessing. Model **386** also includes a further processing function block **390** coupled to memory sub-module **336**, wherein function block **390** facilitates engaging at least one of problem solving sub-module **350**, learning sub-module **340**, and deliberation sub-module **380**.

Also, in the exemplary embodiment, memory sub-module **336** transmits data stored therein as a function of requests by sensory input sub-module **306**, preprocess function block **388**, perception sub-module **322**, and further processing function block **390**. Sensory input sub-module **306** requests and receives data, including, without limitation, missing data **392** that includes, without limitation, data that is missing, but needed, and is resident within memory sub-module **336**. Preprocess function block **388** requests and receives data, including, without limitation, priming data **394** that includes, without limitation, data that facilitates filtering and preprocessing of the information received by sensory input sub-module **306**.

Further, in the exemplary embodiment, perception sub-module **322** requests and receives data, including, without limitation, internal data **394** that includes, without limitation, data and models that are internal to system **200**. Perception sub-module **322**, through comparison sub-module **332**, compares sensory input data **324** with associated internal data **394** and models and determines if there is a positive match, a positive mismatch, or no associated internal data (indicative of a novel input), and directs a request to further processing function block **390**. Function block **390** requests the necessary data from memory sub-module **336** and function block **390** directs the data to at least one of problem solving sub-module **350**, learning sub-module **340**, and deliberation sub-module **380**.

In general, perception sub-module **322** has a perception of time, i.e., system **200** can analyze data as a function of the fourth dimension, i.e., time. Time is perceived because system **200** perceives events, retains memories of those events, and forms an episodic sense of time as a result of the memories. For example, system **200** has the ability to estimate long durations of time and short intervals of time and discern the difference therebetween. Also, system **200** facilitates a perceived speed of time typically associated with humans, e.g., time seems to pass slowly when anxiously waiting for an uncheerful event to happen, and time seems to pass more quickly when cheerful events are occurring.

In the context of an asset management example, for sensory input from a planner interface (not shown, but similar to user input interface **130** shown in FIG. **1**), a planner (including, without limitation, user **125** (shown in FIG. **1**) and operators **230** and **235** (human or machine) (both shown in FIG. **2**)) inputs a selected arrival time of 4:00 p.m. CST on Dec. 21, 2012 for a cargo shipment that is too close to the actual time of the request, i.e., 3:15 p.m. CST on Dec. 21, 2012). To make that temporal proximity determination, system **200** takes into consideration the distance between an origin of the trip, i.e., New York City, USA, and the destination, i.e., Chicago, USA, as well as the anticipated time required for loading the cargo at the warehouse. Perception sub-module **322** generates a request for comparison sub-module **332** to compare the desired time of arrival and the time of request (as input) with the estimated time from loading plus the trip duration from the origin to destination, wherein such data is requested from memory sub-module **336**.

An avatar (not shown) will be generated on the planner interface and will request additional information from the planner, thereby showing perceptive features to the planner. The avatar will talk back to the planner and ask if the planner really meant the cargo arrival time at 4:00 p.m. CST on Dec. 21, 2012, and explain to the planner that the delivery to Chicago from New York City will take much longer than 15 minutes. Also, system **200** uses its adaptive learning features to determine trends and patterns associated with the planner, make determinations if the input or requests are inconsistent, and ask the planner if there is an error or if the request is new.

Also, in the context of an asset management example, if the planner inputs that there is a blizzard in Arizona, USA, system **200** will perceive that there is an error and/or inconsistency by comparing the planner's input in comparison sub-module **332** with historical weather patterns for the region resident in memory sub-module **336**. An avatar will inform the planner that such weather is not reasonable and request a confirmation or a correction. In the event that the planner is also planning a cargo shipment originating in New York City, and New York City is experiencing a blizzard, system **200** will recognize the origin of the error, and will ask the planner if the blizzard information was for New York City rather than Arizona.

Further, in the context of an asset management example, if a problem with a cargo shipment comes to the attention of system **200**, system **200** will perceive the feedback from the receiver and compare it with the feedback from the planner. Also, system **200** will also perceive the trends in response from the receiver and the planner concerning the problem and push the problem resolution to learning sub-portion **340**.

Moreover, in the context of an asset management example, robots in a warehouse can perceive changes in the warehouse environment, including, without, limitation, the absence of an expected item in inventory.

FIG. **5** is a flow chart of an exemplary model **398** of comparison data flow that may be used with adaptive cognitive system **200**. In the exemplary embodiment, comparison sub-module **332** is directly or indirectly coupled to each of problem solving sub-module **350**, perception sub-module **322**, deliberation sub-module **380**, sensory input sub-module **306**, emotion sub-module **330**, memory sub-module **336** and learning sub-module **340**. Comparison sub-module **332** is requested by those other portions of system **200** to perform data comparisons as needed. Comparison sub-module **332** returns a comparison output to the component that requested the comparison. For example, as described above for perception sub-module **322**, comparison sub-module **332** compares sensory input data **324** with associated internal data **394** and determines if there is a positive match, a positive mismatch, or no associated internal data (indicative of a novel input), and directs a request to further processing function block **390** (shown in FIG. **4**).

In the context of an asset management example, for sensory input from a planner interface or a receiver interface (neither shown, but both similar to user input interface **130** shown in FIG. **1**), a planner (including, without limitation, user **125** (shown in FIG. **1**) and operators **230** and **235** (human or machine) (both shown in FIG. **2**)), the sensory input is compared with a model of expected input, e.g., without limitation, previous orders and delivery times. An unusual order may trigger a different perception, e.g., an avatar (not shown) may request an order confirmation.

Also, in the context of an asset management example, incoming data **324** (shown in FIG. **3**) from sources other than human are treated like any sensory input, i.e., the data can be compared with expected values, e.g., expected weather by season, wherein system **200** can change perceptions or trigger emotions in response to such data **324**. Further, in the context of an asset management example, warehouse robots could compare conditions from their sensory input devices (not shown), e.g., without limitation, bump sensors and pointing lasers, and compare with an internally-embedded map of the warehouse environment.

FIG. **6** is a flow chart of an exemplary functional logic architecture **400** that may be used with intelligent, neuromorphic, cognitive, system **200**. FIG. **7** is a view of functional logic architecture **400** in relationship to high-level cognitive architecture **300**. In the exemplary embodiment, a material shipping example is used to illustrate the interaction of portions of high-level cognitive architecture **300** and functional logic architecture **400**.

Functional logic architecture **400** includes two sequences, i.e., a production sequence **402** and a learning sequence **404**. Production sequence **402** facilitates operation of system **200** to control at least a portion of the environment of real world **304** (shown in FIG. **3**) to achieve a goal of system **200**. Learning sequence **404** facilitates a training process that generates an inventory of success-oriented models based on historical data including, without limitation, positive outcomes and the negative outcomes.

Production sequence **402** includes a START function block **410** that requires at least some user information, e.g., a shipping origin and a shipping destination. Sequence **402** also includes an input capture function block **412** coupled to a plurality of data registers **414** that include data, e.g., the latitudes and longitudes of the shipping origin and shipping destination. Data registers **414** are input entities as described above, and registers **414** may be resident within an external system, e.g., an Internet-based mapping/GPS application. Sequence **402** further includes a data check function block **416** that verifies that the necessary inputs to initiate the shipping process are available and that the data is complete. Such verification of data completeness represents one aspect of data preprocessing as used by system **200**. If the data from registers **414** is determined to be incorrect, a request for user input **418** is transmitted to at least one of user **125** (shown in FIG. **1**) and first operator **230** and second operator **235** (human or machine) (both shown in FIG. **2**). In the exemplary embodiment, user **125** and operators **230** and **235** are input entities as described above. Function blocks **410**, **412**, and **416**, registers **414**, and request for user input **418** are associated with sensory input sub-module **306** and perception sub-module **322**.

Production sequence **402** also includes an input comparison function block **420** that compares the validated input values. i.e., verified for completeness, against upper and lower parameters such that the accuracy of the data is verified. A lookup action **422** is performed, i.e., system **200** executes a lookup within memory sub-module **336** by requesting data from registers **424**, e.g., upper and lower parameters for the latitude and longitude data provided as described above. If the data is determined to be invalid, request for user input **418** is invoked as described above.

Production sequence **402** further includes a memory verification function block **426** that performs a lookup action **428** in memory sub-module **336** to determine if the parameter-validated data is stored in data register **430** located in memory sub-module **336**. For example, system **200** will determine if the data associated with the shipping origin and the shipping destination are in memory sub-module **336**. Input comparison function block **420** and memory verification function block **426** are associated with perception sub-module **322** and comparison sub-module **332**.

If the data is not in memory sub-module **336**, production sequence **402** includes a sensory input agent function block **432** that searches for the correct information. Function block **432** is associated with deliberation sub-module **380** and action sub-module **310**. For a specific deficiency, e.g., missing location data, a potential solution **353** (shown in FIG. **3**) is generated. One example of a potential solution **353** is "looking on the Internet for the missing data." A similar course of action **384** (shown in FIG. **3**) is decided upon, and directions **311** (shown in FIG. **3**) are executed in real world **304** to input such data **318** (shown in FIG. **3**) into sensory input sub-module **306**. Once the data is received by sensory input sub-module **306**, the data is transmitted to registers **430** through a store action **434**. Alternatively, for such simple activities, such as a data request, the data request may be executed through reflex sub-module **308** to generate an autonomic response **309**.

Production sequence **402** also includes a cluster determination function block **436** that generates data clusters C_i, wherein i represents any whole number greater than 0, and up to N clusters. Data clusters C_i are defined as a function of at least one attribute, wherein the attributes that define the C_i are one of similarity and dissimilarity. While system **200** endeavors to generalize the attributes, e.g., package dimensions and/or weight, and inclement weather, system **200** generates data clusters C_i that also facilitate granularity, accuracy, and scalability. Methods and mechanisms for clustering are described further below. If the data requested in function block **426** is in data registers **430**, cluster determination function block **436** receives the data and generates a data cluster C_i defined by the attributes of that data.

Production sequence **402** further includes a model M_i retrieval function block **438** that is configured to execute a lookup action **440** within registers **442** in memory sub-module **336** for any models M_i that are associated with cluster C_i. Models M_i are formed within system **200** using at least a portion of a data cluster C_i and are stored in memory sub-module **336**. Methods and mechanisms for modeling are described further below. In the exemplary embodiment, there is a one-to-one relationship between a cluster C_i and a model M_i. Alternatively, any relationship between clusters C_i and models M_i is used that enables operation of system **200** as described herein, including, without limitation, one-to-many and many-to-many. Since system **200** strives to generalize the attributes of cluster C_i model M_i derived from a generalized-attribute cluster C_i also includes generalized attributes. In the exemplary embodiment, model M_i includes attributes of shipping origin latitude (LatOrig.), longitude (LongOrig.), and regional origin (RegOrig.). Model M_i also includes attributes of destination latitude (LatDest.), longitude (LongDest.), and regional destination (RegDest).

If the associated model M_i is located in memory sub-module **336**, the data is plugged into model M_i through a data plug-in function block **444**. If an associated model M_i is not found, a model lookup function block **446** searches through memory sub-module **336** for a model M_i that includes data attributes derived from a similar data cluster. If such a model M_i is found, the data is plugged into the similar model M_i through data plug-in function block **444**. Cluster determination function block **436**, model retrieval function block **438**, and data plug-in function block **444** are associated with learning sub-module **340** and problem solving sub-module **350**.

Regardless of how found, once a model M_i is located, the data is plugged into model M_i through data plug-in function block **444** and an output function block **448** transmits the information required by one of user **125**, first human/machine operator **230**, and second human/machine operator **235**, e.g., an estimated time of arrival (ETA) of the shipment at the destination. If no models are found, a message function block **450** alerts at least one of user **125**, first operator **230**, and second operator **235** to the fact that system **200** is not able to provide the information requested and system **200** will collect data to form into new clusters that will subsequently be used to form new models. Output function block **448** and message function block **450** are associated with action sub-module **310**.

Learning sequence **404** includes a START function block **460** that utilizes at least some user information to initiate the training process, e.g., a shipping origin and a time of shipping, and a shipping destination and a time of arrival. Sequence **404** also includes an input capture function block **462** coupled to a plurality of data registers **464** that include data, e.g., the latitudes and longitudes of the shipping origin and shipping destination. Data registers **464** are input entities as described above, and registers **464** may be resident within an external system, e.g., an Internet-based mapping/GPS application. Sequence **404** further includes a data check function block **466** that verifies that the necessary inputs to initiate the shipping process are available and that the data is complete. Such verification of data completeness represents one aspect of data preprocessing as used by system **200**. If the data from registers **464** is determined to be incorrect, a rejection **468** is transmitted to at least one of user **125** (shown in FIG. **1**) and first operator **230** and second operator **235** (human or machine) (both shown in FIG. **2**). In the exemplary embodiment, user **125** and operators **230** and **235** are input entities as described above. Also, in the event of rejection **468**, learning sequence **404** is terminated. Function blocks **460**, **462**, and **466**, registers **464**, and rejection **468** are associated with sensory input sub-module **306** and perception sub-module **322**.

Learning sequence **404** also includes an input comparison function block **470** that compares the validated input values, i.e., verified for completeness, against upper and lower parameters such that the accuracy of the data is verified. A lookup action **422** is performed, i.e., system **200** executes a lookup within memory sub-module **336** by requesting data from registers **424**, e.g., upper and lower parameters for the latitude and longitude data provided as described above. If the data is determined to be invalid, rejection **468** is invoked as described above.

Learning sequence **404** further includes a memory verification function block **476** that performs a lookup action **478** in memory sub-module **336** to determine if the parameter-validated data is stored in data register **430** located in memory sub-module **336**. For example, system **200** will determine if the data associated with the shipping origin and the shipping destination are in memory sub-module **336**. Input comparison function block **420** and memory verification function block **426** are associated with perception sub-module **322** and comparison sub-module **332**. The remainder of learning sequence **404** is associated with learning sub-module **340**.

If the data is not in memory sub-module **336**, learning sequence **404** includes a sensory input agent function block **482** that searches for the correct information. For a specific deficiency, e.g., missing location data, a potential solution **353** (shown in FIG. **3**) is generated. One example of a potential solution **353** is "looking on the Internet for the missing data." A similar course of action **384** (shown in FIG. **3**) is decided upon, and directions **311** (shown in FIG. **3**) are executed in real world **304** to input such data **318** (shown in FIG. **3**) into sensory input sub-module **306**. Once the data is received by sensory input sub-module **306**, the data is transmitted to registers **430** through a store action **484**. Alternatively, for such simple activities, such as a data request, the data request may be executed through reflex sub-module **308** to generate an autonomic response **309**.

Learning sequence **404** also includes a model building function block **486** that is configured to build a model M_i for a cluster C_i of data collected as a result of lookup action **478**. Learning sequence **404** further includes a model lookup function block **488** that performs a lookup action **490** in data registers **442** of memory sub-module **336**. In the exemplary embodiment, model M_i includes attributes of shipping origin latitude (LatOrig.), longitude (LongOrig.), regional origin (RegOrig.), and time of shipping (tOrig.) Model M_i also includes attributes of destination latitude (LatDest.), longitude (LongDest.), regional destination (RegDest.), and time of delivery (tDest).

If model M_i does not reside within data registers **442**, the model M_i is stored therein through a store action **492** and a storage function block **494**. If a model similar to model M_i resides within data registers **442**, a model comparison function block **496** compares the two models. If the models are sufficiently different, a decision function block **498** executes one of three options. A first option is to store the new model M_i and keep the old model. A second option is to store the new model M_i and discard the old model. A third option is to discard the new model M_i and keep the old model. Regardless of the option selected, or if function block **496** determines the models to be sufficiently similar, a sequence termination function block **499** ends the operation.

In the exemplary embodiment, lookup actions **422**, **428**, **440**, **472**, **478**, and **490** are performed using the SDM features of memory sub-module **336**.

FIG. **8** is a schematic view of an exemplary learning subsystem architecture **500** that may be used with functional logic architecture **400** in relationship to high-level cognitive architecture **300**. Learning subsystem architecture **500** performs adaptive on-line learning of adaptive cognitive system **200**. FIG. **8** shows a portion of functional logic architecture **400**, i.e., learning subsystem **500**, with greater granularity.

In the exemplary embodiment, model building function block **486** is associated with learning sub-module **340**. Also, model lookup function block **488** and model comparison function block **496** are associated with comparison sub-module **332**. Further, decision function block **498** is associated with deliberation sub-module **380**. Moreover, storage function block **494** is associated with memory sub-module **336**.

FIG. **9** is a schematic view of an exemplary problem solving subsystem architecture **550** that may be used with functional logic architecture **400** in relationship to high-level cognitive architecture **300**. Problem solving subsystem architecture **550** cooperates with learning subsystem architecture **500** (shown in FIG. **8**) to execute adaptive on-line learning of adaptive cognitive system **200**. FIG. **8** shows a portion of functional logic architecture **400**, i.e., problem solving subsystem **550**, with greater granularity.

In the exemplary embodiment, cluster determination function block **436** and model retrieval function block **438** are associated with comparison sub-module **332**. Also, data plug-in function block **444** is associated with action sub-module **310**. Further, model lookup function block **446** is associated with deliberation sub-module **380**.

Referring to FIGS. **3**, **8**, and **9** together, learning subsystem **500** and problem solving subsystem **550** together include comparison sub-module **332**, memory sub-module **336**, learning sub-module **340**, deliberation sub-module **380**, and action sub-module **310** to leverage feedback **314** from real world **304** to facilitate system **200** in self-adapting through learning and problem solving mechanisms. Feedback **314** is based on either actions that system **200** took or changes in the associated environment of real world **304** due to other external events either from the environment or other agents interacting with system **200**.

In the exemplary embodiment, learning subsystem **500** and problem solving subsystem **550** cooperate to use at least one of three learning modes, i.e., supervised leaning mode, semi-supervised learning mode, and reinforcement learning mode. To facilitate continuous learning within system **200**. Supervised learning mode defines a class of machine learning techniques. Supervised learning mode uses supervised training methods to generate sets of clusters C_i and models M_i from supervised training data, i.e., labeled input data wherein associated desired output values are provided with the training data. User-controlled labeled data insertion into learning sequence **404** (shown in FIG. **6**) is an example of the supervised learning mode.

Semi-supervised learning mode defines a class of machine learning techniques that make use of both labeled and unlabeled data for training, wherein at least a portion of the input training data is labeled data and the remainder of the training data is unlabeled data. User-controlled labeled and unlabeled data insertion into learning sequence **404** (shown in FIG. **6**) is an example of the semi-supervised learning mode. Moreover, insertion of user-inserted labeled data and unlabeled numerical data collected through sensory input sub-module **306** facilitates system **200** adaptively learning by generating sets of clusters C_i and models M_i from both the labeled and unlabeled training data.

Reinforcement learning mode defines a class of machine learning techniques that is concerned with how an agent ought to take actions in an environment so as to maximize some notion of reward. In the exemplary embodiment, system **200** uses reinforcement learning techniques that are based on reward or penalties to generate an emotional response from emotion sub-module **330**. Also, emotion sub-module **330** responds to criticisms from either real world **304** or an input entity, i.e., a human or another system.

Referring to FIGS. **8** and **9**, lookup action **440** (associated with model retrieval function block **438**) and lookup action **490** (associated with model lookup function block **488**) are performed using the SDM features of memory sub-module **336**. Also, learning sub-module **340** (associated with model building function block **486**) uses at least one of an artificial neural network (ANN) and a support vector machine (SVM) to execute the assigned functions. Further, comparison sub-module **332** (associated with model comparison function block **496** and cluster determination function block **436**) uses a SVM to execute the assigned functions. Moreover, deliberation sub-module **380** (associated with model lookup function block **446**) uses a genetic algorithm (GA) to execute the assigned functions. ANNs, SVMs, and GAs are discussed further below.

FIG. **10** is a flow chart of an exemplary input and output (I/O) architecture **600** that may be used with functional logic architecture **400** (shown in FIGS. **6** and **7**). More specifically, I/O architecture **600** represents the I/O data flow associated with learning activities of system **200**. Learning in system **200** involves both focused attention to the data flow associated with the learning process and peripheral perception, i.e., the ability to recognize pertinent data while not necessarily focusing on such data.

In at least some embodiments, adaptive cognitive system **200** is defined by three functional layers in a model-view-controller (MVC) pattern. The three layers are the Web user interface (UI) layer (for the "view"), a controller middle layer (for the "controllers"), and algorithms (for the "model"). As is known in the art of computing system design and implementation, a variety of methods to implement a system are available. The plurality of input entities in real world **304** and edge module **302** (both shown in FIG. **3**), including, without limitation, plurality of edge devices **303** (shown in FIG. **3**) that facilitate coupling of system **200** to real world **304** (shown in FIG. **3**), and sensory input sub-module **306** (shown in FIG. **3**) configured to receive inputs from the input entities.

Also, in at least some embodiments, without limitation, Java® is used to implement the middle layer, and system **200** operates in a plurality of modes including a learning mode, a forecasting mode, and a deliberation mode. These three modes include a plurality of decision points. The modes and decision points are described in detail below.

In the exemplary embodiment, and in the context of asset management, and more specifically, supply chain management, I/O architecture **600** includes a fleet database **602**, a traffic service **604**, and a weather service **606** coupled to a data processing node **608**. Alternatively, any type inputs and any number of inputs are used that enable operation of system **200** as described herein. Fleet database **602**, traffic service **604**, weather service **606** and data processing node **608** are associated with perception sub-module **322** and comparison sub-module **332** (both shown in FIG. **3**). Also, the data inputs from fleet database **602**, traffic service **604**, and weather service **606** are transmitted through sensory input sub-module **306** in edge module **302** (both shown in FIG. **3**). Such data processing in system **200** creates an input file structure (not shown) within a system database **610**, and preprocesses the data into valid trips.

Also, in the exemplary embodiment, data from system database **610** is transmitted to an SVM clustering node **612** that is configured through a SVM configuration manager **614**. SVM clustering node **612** is coupled to a system learning controller **615** that is configured through a system learning configuration sub-module **616**. SVM clustering node **612** and SVM configuration manager **614** are associated with at least one clustering algorithm (discussed further below). SVM clustering node **612** generates data clusters (not shown) based on at least one data attribute and transmits the data clusters to a system deliberation node **618**. Clustering of trips is typically based on similarities that include, without limitation, region, time, weather conditions, and traffic conditions. System deliberation node **618** is coupled to a plurality of old data clustering output registers **620**, wherein the data cluster outputs from node **612** are evaluated against older data clusters, and if necessary, a decision is made as to whether the new data clusters may be transmitted as is, modified, or deleted. System deliberation node **618** transmits the new data clusters to a plurality of new data clustering output registers **622**. Node **618** and registers **620** and **622** are associated with deliberation sub-module **380** (shown in FIG. **3**).

The new data clustering output is transmitted from registers **622** to at least one of three branches, i.e., to a genetic algorithm (GA) branch **624**, an artificial neural network (ANN) branch **626**, and a SVM learning branch **628**. GA branch **624** includes a GA node **630** coupled to learning sub-module **340**, new data clustering output registers **622**, and a GA configuration manager **632**. GA node **630** generates

a model based on the clustered data input, for example, without limitation, a shipping itinerary for a package. The model output is transmitted to a system deliberation node **634**. System deliberation node **634** is coupled to a plurality of old GA output registers **636**, wherein the GA model outputs from node **630** are evaluated against older GA models, and if necessary, a decision is made as to whether the new GA models may be transmitted as is, modified, or deleted. System deliberation node **634** transmits the new GA models to a plurality of new GA output registers **638**.

ANN branch **626** includes an ANN node **640** coupled to learning sub-module **340**, new GA output registers **638**, and an ANN configuration manager **642**. ANN node **640** generates a forecast based on the model input, for example, without limitation, an ETA for delivery of a package. The forecast output is transmitted to a system deliberation node **644**. System deliberation node **644** is coupled to a plurality of old ANN output registers **646** and a plurality of old ANN learning model registers **648**, wherein the ANN forecast outputs from node **640** are evaluated against older ANN forecasts, and if necessary, a decision is made as to whether the new ANN forecasts may be transmitted as is, modified, or deleted. System deliberation node **644** transmits the new ANN forecasts to a plurality of new ANN output registers **650** and a new ANN model register **652**.

SVM branch **628** includes a SVM learning node **654** coupled to new data clustering output registers **622** and a SVM learning configuration manager **656**. SVM learning node **654** generates a learning model output that is transmitted to a system deliberation node **634**. System deliberation node **634** is coupled to a plurality of old SVM learning output registers **658** and a plurality of old SVM learning model registers **660**, wherein the SVM learning model outputs from node **656** are evaluated against older SVM learning models, and if necessary, a decision is made as to whether the new SVM learning model outputs may be transmitted as is, modified, or deleted. System deliberation node **634** transmits the new SVM learning model outputs to a plurality of new SVM learning output registers **662** and a new SVM learning model register **664**. The new SVM learning model outputs are primarily used for forecasting and clustering.

Operation of I/O architecture **600** of system **200** is facilitated by a controller hierarchy (not shown). There are four controllers, i.e., a system controller, learning controller **615**, a forecasting controller, and a deliberation controller. Learning controller **615** is the controlling authority for the learning mode of system **200**. It invokes the corresponding SVM configuration manager **614**, system learning configuration manager **616**, and SVM learning configuration manager **656** for the execution of the associated learning processes. The forecasting controller is the controlling authority for the forecasting mode of system **200**. It invokes the corresponding GA configuration manager **632**. The forecasting controller creates the input file from the inputs provided by a UI (the first layer), e.g., without limitation, Web UI, and controls ANN branch **626**, including ANN configuration manager **642**, when system **200** is in forecasting mode. The deliberation controller is the controlling authority for the deliberation mode of system **200**, i.e., it controls system deliberation nodes **618**, **634**, **644**, and **656**. The system controller is the main controller and controls the other three controllers.

FIG. **11** is a flow chart of an exemplary implementation of a learning controller sequence **700** that may be used with I/O architecture **600** (shown in FIG. **8**). FIG. **12** is a flow chart of an exemplary support vector machine (SVM) clustering sequence **702** of learning controller sequence **700**. FIG. **13** is a flow chart of an exemplary artificial neural network (ANN) and genetic algorithm (GA) sequence **704** of learning controller sequence **700**. FIG. **14** is a flow chart of an exemplary SVM learning sequence **706** of learning controller sequence **700**.

In at least some embodiments, learning controller sequence **700**, i.e., the sequence of operations associated with system learning controller **615** when system **200** is in the learning mode, uses a plurality of algorithms implemented in the third layer of system **200**, thereby providing the "model" portion of the model-view-controller (MVC) pattern. As is known in the art of computing system design and implementation, a variety of methods to implement a system are available. Also, in general, the middle layer is developed in Java® while the third, i.e., algorithm layer is developed using C++. The interaction between Java® and C++ is achieved using Java® Native Interface (JNI). Alternatively, any computer languages are used in any configuration that enable operation of system **200** as described herein.

Referring to FIG. **11**, in the exemplary embodiment, learning controller sequence **700** includes SVM clustering sequence **702**, ANN and GA sequence **704**, and SVM learning sequence **706**. SVM clustering sequence **702** includes system learning controller **615**, a database processing agent **708**, a SVM clustering manager **710**, and a SVM clustering sub-sequence **712**. ANN and GA sequence **704** includes a GA manager **714**, a GA sub-sequence **716**, an ANN manager **718**, and an ANN sub-sequence **720**. SVM learning sequence **706** includes a SVM learning manager **722** and a SVM learning sub-sequence **724**. While a particular sequence using SVM, ANN, and GA is described herein, as is known in the art of computing system design and implementation, a variety of methods to implement a system are available. Therefore, some embodiments use any sequence of SVM, ANN, and GA, including only one or two of the three, that system **200** deems necessary for the current operational issues being managed by system **200**. Moreover, while SVM, ANN, and GA are described herein in detail, other sequences may be used to enable operation of system **200** as described herein.

In the exemplary embodiment, learning controller sequence **700** includes five managers, i.e., SVM clustering manager **710**, GA manager **714**, ANN manager **718**, SVM learning manager **722**, and an abstract manager (not shown) that implements the basic functionality of managers **710**, **714**, **718**, and **722**, wherein managers **710**, **714**, **718**, and **722** inherit the functionality of the abstract manager. Managers **710**, **714**, **718**, and **722** facilitate thread management and the associated logic. In the exemplary embodiment, thread management is facilitated through dynamic thread creation, wherein the threads are created as they are needed and once the thread finishes its execution, the thread is destroyed. Alternatively, thread management is facilitated through a thread pool, wherein a thread pool is created during initialization of system **200**, or the learning mode thereof, and the threads are used from this pool as, and when, required. The threads are created in the thread pool in a suspend status and they will be active whenever there is a request for the thread.

In the exemplary embodiment, each thread class implements JNI functions for bi-directional interaction with C++ dlls to facilitate bi-directional communication between C++ dlls in the third layer and Java® in the second layer. The threads are created and managed by algorithms implemented specifically for each associated thread.

Also, in the exemplary embodiment, system learning controller **615** starts each of SVM clustering manager **710**, GA manager **714**, ANN manager **718**, SVM learning manager **722** in the learning mode. Managers **710**, **714**, **718**, and **722** wait for input files to be transmitted into their respective input

directories. For example, data processing agent **708** transmits the necessary input files to SVM clustering sequence **712** for clustering the received data and SVM clustering sequence **712** generates data clusters based on the data input received using an SVM clustering algorithm. The output, i.e., data clusters of SVM clustering sub-sequence **712** is the input for GA manager **714** and GA sub-sequence **716** that generate at least one model from the data clusters using a GA algorithm. The output, i.e., models of GA sub-sequence **716** is the input for ANN manager **718** and ANN sub-sequence **720**. ANN manager **718** and ANN sub-sequence **720** receives the input models from GA sub-sequence **716**, processes the models, and produces an output, e.g., a forecast using an ANN algorithm. This forecast is normally used for the forecasting mode of system **200**. Moreover, SVM learning manager **722** and SVM learning sub-sequence **724** include an SVM learning algorithm, which runs parallel to GA sub-sequence **716** and ANN sub-sequence **720**. SVM learning manager **722** receives the output, i.e., data clusters of SVM clustering sub-sequence **712** and generates a model that can be used for forecasting and clustering.

Referring to FIG. **12**, the interaction of system learning controller **615** and SVM clustering manager **710** and SVM clustering sub-sequence **712** in SVM clustering sequence **702** is shown. Execution of SVM clustering sequence **702** is closely associated with SVM clustering node **612** (shown in FIG. **10**). In operation, system learning controller **615** reads **726** system learning configuration parameters from system learning configuration manager **616** (shown in FIG. **8**) into memory sub-module **336** (shown in FIG. **3**) and invokes **727** database processing agent **708**. Database processing agent **708** reads **728** the database processing agent configuration parameters into memory sub-module **336** and invokes **729** SVM clustering manager **710**. Database processing agent **708** executes **730** a lookup for data in system database **610** (shown in FIG. **10**), processes and at least partially clusters **732** the data called from database **610**, and copies **734** the data to an SVM clustering input directory (not shown). Operation of database processing agent **708** is then completed **736**, i.e., database processing agent **708** is "killed" **737**.

Also, in operation, SVM clustering manager **710** is fed-forward the command to execute **730** a lookup for data in system database **610** from database processing agent **708**. Such execution **730** facilitates SVM clustering manager's **710** anticipation of data receipt therefrom, i.e., SVM clustering manager **710** monitors **738** the SVM clustering input directory for data files transmitted from database processing agent **708**. The features of the abstract manager (not shown) are extended into SVM clustering manager **710** and manager **710** provides the functionality for incoming data monitoring and thread management. SVM clustering manager **710** generates **740** at least one thread (not shown) for SVM clustering using a SVM clustering algorithm. SVM clustering manager also creates **741** at least one SVM clustering object to facilitate generating the desired data clusters. The number of threads created will be based on the number of data files that will be processed in SVM clustering sequence **702**.

Further, in operation, SVM clustering sub-sequence **712** is initiated through receipt of the clustering object. In SVM clustering sub-sequence **712**, the SVM clustering configuration parameters are read **742** into memory sub-module **336** and the data files from the SVM clustering input directory are read **744** into memory sub-module **336**. The SVM clustering data is processed **746** to define at least one data cluster for use within ANN and GA sequence **704** (shown in FIG. **11**). The data clusters are stored **748** in the SVM clustering output directory (not shown).

Moreover, in operation, once the data clusters are stored **748**, operation of SVM clustering processing is completed **750**, the SVM clustering object is "destroyed" **752** and the SVM clustering thread is either "killed" or "suspended" **754**. Operation of SVM clustering interface processing is then completed **756**, i.e., SVM clustering manager **710** is "killed" **757**.

Referring to FIG. **13**, the interaction of system learning controller **615** and GA manager **714**, GA sub-sequence **716**, ANN manager **718**, and ANN sub-sequence **720** in ANN and GA sequence **704** is shown. Execution of GA sub-sequence **716** is closely associated with GA node **630** (shown in FIG. **10**) and execution of ANN sub-sequence **720** is closely associated with ANN node **640** (shown in FIG. **10**). In operation, system learning controller **615** reads **802** system learning configuration parameters from system learning configuration manager **616** (shown in FIG. **10**) into memory sub-module **336** (shown in FIG. **3**) and invokes **803** GA manager **714**. The features of the abstract manager (not shown) are extended into GA manager **714** and manager **714** provides the functionality for incoming data monitoring and thread management. GA manager **714** monitors **804** the SVM clustering output directory (not shown) for data clusters stored **748** (shown in FIG. **10**) in the SVM clustering output directory.

Also, in operation, GA manager **714** generates **806** at least one thread (not shown) for GA model formation using a GA algorithm. GA manager **714** also creates **807** at least one GA object to facilitate generating the desired models. The number of threads created will be based on, for example, without limitation, the number of data files that will be processed in GA sub-sequence **716**.

Further, in operation, GA sub-sequence **716** is initiated through receipt of the GA object. In GA sub-sequence **716**, the GA configuration parameters are read **808** into memory sub-module **336** and the data files from the SVM clustering output directory are read **810** into memory sub-module **336**. The SVM clustering output data is processed **812** to define at least one data model for use within ANN sub-sequence **720**. The data models are stored **814** in the GA output directory (not shown).

Moreover, in operation, once the data models are stored **814**, the GA processing is completed **816**, the GA object is "destroyed" **817** and the GA thread is either "killed" or "suspended" **818**. Operation of GA interface processing is then completed **820**, i.e., GA manager **714** is "killed" **821**.

Continuing to refer to FIG. **13**, in operation, system learning controller **615** reads **802** system learning configuration parameters from system learning configuration manager **616** into memory sub-module **336** and invokes **822** ANN manager **718**. The features of the abstract manager (not shown) are extended into ANN manager **718** and manager **718** provides the functionality for incoming data monitoring and thread management. ANN manager **718** monitors **824** the GA output directory for data models stored **814** in the GA output directory.

Also, in operation, ANN manager **718** generates **826** at least one thread (not shown) for ANN model formation using an ANN algorithm. ANN manager **718** also creates **827** at least one ANN object to facilitate generating the desired models. The number of threads created will be based on, without limitation, the number of data files that will be processed in ANN sub-sequence **720**.

Further, in operation, in ANN sub-sequence **720**, the ANN configuration parameters are read **828** into memory sub-module **336** and the data files from the GA output directory are read **830** into memory sub-module **336** and the data files from the SVM clustering output directory are read **832** into memory sub-module **336**. The GA output data and the SVM clustering output data is processed **834** to define at least one data model for forecasting and clustering use within system **200**. The data models are stored **836** in the ANN output directory (not shown) and stored **838** in memory **336**.

Moreover, in operation, once the data models are stored **836** and **838**, the ANN processing is completed **840**, the ANN object is "destroyed" and the ANN thread is either "killed" or "suspended" **842**. Operation of ANN interface processing is then completed **844**, i.e., ANN manager **718** is "killed" **845**.

Referring to FIG. **14**, the interaction of system learning controller **615** and SVM learning manager **722** and SVM learning sub-sequence **724** in SVM learning sequence **706** is shown. Execution of SVM learning sub-sequence **722** is closely associated with SVM learning node **654** (shown in FIG. **10**). In operation, system learning controller **615** reads **902** system learning configuration parameters from system learning configuration manager **616** (shown in FIG. **10**) into memory sub-module **336** (shown in FIG. **3**) and invokes **903** SVM learning manager **722**. The features of the abstract manager (not shown) are extended into SVM learning manager **722** and manager **722** provides the functionality for incoming data monitoring and thread management. SVM learning manager **722** monitors **904** the SVM clustering output directory (not shown) for data clusters stored **748** (shown in FIG. **12**) in the SVM clustering output directory.

Also, in operation, SVM learning manager **722** generates **906** at least one thread (not shown) for SVM learning using a SVM learning algorithm. SVM learning manager **722** also creates **907** at least one SVM learning object to facilitate generating the desired models. The number of threads created will be based on, without limitation, the number of data files that will be processed in SVM learning sub-sequence **724**.

Further, in operation, in SVM learning sub-sequence **724**, the SVM learning configuration parameters are read **908** into memory sub-module **336** and the data files from the SVM clustering output directory are read **910** into memory sub-module **336**. The SVM clustering output data is processed **912** to define at least one data model for training and forecasting use within system **200**. The data models are stored **914** in the SVM learning output directory (not shown) and stored **916** in memory **336**.

Moreover, in operation, once the data models are stored **914** and **916**, the SVM learning processing is completed **918**, the ANN object is "destroyed" **919**, and the ANN thread is either "killed" or "suspended" **920**. Operation of SVM learning interface processing is then completed **922**, i.e., SVM learning manager **722** is "killed" **923**.

FIG. **15** is a flow chart of an exemplary model **1000** of generalized continuous learning that is integral to adaptive cognitive system **200**. In the exemplary embodiment, raw data **324** representative of real world **304** (shown in FIG. **3**) is received by sensory input sub-module **306**. Raw data **324** includes event data **1002** that is representative of feedback **314** (shown in FIG. **3**) from real world **304** as a function of directives **311** transmitted from action sub-module **310** (both shown in FIG. **3**). Perception sub-module **322** receives raw data **324** from sensory input sub-module **306** and extracts event data **1002** from raw data **324**. Also, external, dynamic, relevant, contextual data **318** is received by sensory input sub-module **306**, wherein such data **318** includes, without limitation, real-time data weather and traffic data received from weather service **606** and traffic service **604** (both shown in FIG. **10**). Perception sub-module **322** receives contextual data **318** and integrates event data **1002** with contextual data

318 to form portion **342** of incoming data **318** and **324**, thereby executing actions associated with data processing node **608** (shown in FIG. **10**).

Also, in the exemplary embodiment, data portion **342** is transmitted to learning sub-module **340** from perception sub-module **322**. Data clusters are formed based on at least one similar attribute through the use of SVM clustering node **612** (shown in FIG. **10**) and SVM clustering sequence **702** (shown in FIGS. **11** and **12**). The data clusters are used to build an abstract model **1004** for each data cluster through use of GA node **630**, ANN node **640**, and SVM learning node **654** (all three shown in FIG. **10**), and ANN and GA sequence **704** (shown in FIGS. **11** and **13**) and SVM learning sequence **706** (shown in FIGS. **11** and **14**). Each model **1004** is stored with a plurality of models **1006**.

Further, in the exemplary embodiment, when models **1006** are used for subsequent activities, data portions **1002** resulting from such activities are used to either generate new models **1004** or modify existing models **1006**. Therefore, system **200** facilitates a continuous learning loop **1008** that continuously adapts system **200** to dynamic environmental conditions in real world **304**.

FIG. **16** is a flow chart of an exemplary model **1020** of learning during execution of a plan, including adapting to changes in the plan, wherein the plan includes multiple shipping routes and trips, wherein such model **1020** may be used with intelligent, neuromorphic, cognitive system **200**. In the exemplary embodiment, raw telematics data **1022** representative of real world **304** (shown in FIG. **3**) shipping data is received by sensory input sub-module **306** (shown in FIGS. **3** and **15**). Such raw telematics data **1012** includes, without limitation, GPS data and remote diagnostics data, e.g., remaining fuel. Raw telematics data **1022** is transmitted to a preprocessing function block **1024** in perception sub-module **322**. Function block **1024** performs verification of data completeness in a manner similar to that described for data check function block **416** in production sequence **402** (both shown in FIG. **6**) as well as other data preprocessing tasks. The preprocessed data is transmitted to memory sub-module **336** (shown in FIG. **3**) to be at least temporarily stored as valid trip data **1026**. In general, collection of data **1022** uses a focused attention of system **200**, such focused attention facilitating robust learning in system **200**.

Also, in the exemplary embodiment, external, dynamic, relevant, contextual data **1028** is received by sensory input sub-module **306** and transmitted to perception sub-module **322**. Contextual data **1028** includes, without limitation, real-time data weather and traffic data received from weather service **606** and traffic service **604** (both shown in FIG. **10**), geographic information system (GIS) data, and fuel availability and price data. Such contextual data represents at least one peripheral perception feature of system **200**, such peripheral perception facilitating robust learning in system **200**. A data integration function block **1030** in perception sub-module **322** receives contextual data **1028**, integrates the preprocessed data with contextual data **1018**, and extracts similar features of data **1028** to form trip data with attributes **1032**. The attributes may include, without limitation, geographical region, time, weather patterns, traffic patterns, and mileage.

Further, in the exemplary embodiment, trip data with attributes **1032** is transferred and in integrated with contextual data **318** and then all is transmitted to learning sub-module **340** from perception sub-module **322** to a clustering function block **1024**. Clustering function block **1034** includes the functionality described for SVM clustering node **612** (shown in FIG. **10**) and SVM clustering sequence **702** (shown in FIGS. **11** and **12**). Data clusters **1036** of trip data **1032** are formed based on at least one of the similar attributes described above through the use of SVM clustering node **612** (shown in FIG. **10**) and SVM clustering sequence **702** (shown in FIGS. **11** and **12**). Data from each trip from trip **1** to trip N is clustered, wherein N is a whole number. Data clusters **1036** are transmitted to a modeling function block **1038** that includes the functionality of GA node **630**, ANN node **640**, and SVM learning node **654** (all three shown in FIG. **10**), and ANN and GA sequence **704** (shown in FIGS. **11** and **12**) and SVM learning sequence **706** (shown in FIGS. **11** and **14**). Each data cluster **1036** forms a model **1040**, wherein each trip has an associated trip model from trip **1** to trip N. Trip models **1040** may be to used to provide information that includes, without limitation, multi-route planning information and trip time estimation.

FIG. **17** is a flow chart of an exemplary model **1050** of problem solving during derivation of an estimated time of arrival for a route and trip that may be used with the adaptive cognitive system **200**. In the exemplary embodiment, origin and destination data **1052** representative of features of the shipping origin and shipping destination, for example, without limitation, latitudes and longitudes. In general, collection of data **1052** uses a focused attention of system **200**, such focused attention facilitating robust determinations of accurate ETAs by system **200**.

Also, in the exemplary embodiment, external, dynamic, relevant, contextual data **1028** is received by data integration function block **1030**. Contextual data **1028** includes, without limitation, real-time data weather and traffic data received from weather service **606** and traffic service **604** (both shown in FIG. **10**), geographic information system (GIS) data, and fuel availability and price data. Such contextual data represents at least one peripheral perception feature of system **200**, such peripheral perception facilitating robust determinations of accurate ETAs by system **200**. Data integration function block **1030** receives contextual data **1028**, integrates origin and destination data **1052** with contextual data **1018**, and extracts similar features of data **1028** and **1052** to form trip data with attributes **1054**. The attributes may include, without limitation, geographical region, time, weather patterns, traffic patterns, and mileage.

Further, in the exemplary embodiment, a classification function block **1056** receives trip data with attributes **1054** and classifies data **1054** according to at least one of such attributes. The classified data is transmitted to a clustering function block **1058** that is similar to clustering function block **1034** (shown in FIG. **16**) and generates at least one data cluster C_i **1060**, wherein i is any whole number from 1 to N. Data cluster C_i **1060** is transmitted to a model selection function block **1062** that is coupled to storage of trip models **1040**. Function block **1062** selects a trip model **1040** most closely associated with data cluster C_i **1060**. Selected trip model **1040** and trip data with attributes **1054** are transmitted to a model M_i function block **1064** and an ETA **1066** of the associated shipment is generated.

FIG. **18** is a flow chart of an exemplary model **1100** of a decision making process that may be used with adaptive cognitive system **200**. Model **1100** is described in the context of asset management. In the exemplary embodiment, model **1100** includes edge devices **303** that include a plurality of user interfaces **130**. At least one of user interfaces **130** includes a planner interface (not shown). The planner interface allows a user, e.g., without limitation, user **125** (shown in FIG. **1**) and operators **230** and **235** (human or machine) (both shown in FIG. **2**), to specify details about the goods that they are about to ship. Through this interface, they can choose which items they wish to ship, the destinations for those items, the priority of the trip, and other attributes. It is through these attributes that the system chooses a route, and the planner has the ability to accept or reject the given route. After the route has been chosen, the planner will receive updates and alerts about the condition of the cargo.

At least one of user interfaces **130** includes a receiver interface. The receiver interface allows a user, e.g., without limitation, user **125** and human/machine operators **230** and **235**, to act as the receiver of the goods being shipped. Through this interface, the receiver can monitor the status of goods being shipped to their destination, and they can also receive alerts about changes in condition of the goods and arrival time of the shipment. Also, through this interface, they will be able to accept or reject the chosen route.

Also, in the exemplary embodiment, edge devices **303** include at least one event interface **1102**. Event interface **1102** allows a third user, e.g., without limitation, user **125** and human/machine operators **230** and **235**, the ability to interfere with the goods being shipped. The user will be able to add events to the route, which may include weather, traffic, or other conditions. These events will cause the system to "re-think" routes and make decisions during the trip's execution.

Further, in the exemplary embodiment, edge devices **303** include additional data sources **1104** for receipt of contextual data. System **200** has access to such additional data sources **1104** when planning the route. These sources of data can be, but are not limited to, weather, traffic, crime, and maps. These will assist the decision-making ability of the system.

Model **1100** also includes a language area **1110** that facilitates communication between system **200** and real world **304** (shown in FIG. **3**), and within system **200** itself to facilitate thinking, imagination, and planning features of system **200**. Language area **1110** facilitates use of avatars (not shown) capable of speech to communicate to system users through user interfaces **130**. The avatars are also capable of facial expressions and vocal intonations to express emotion. Language area **1110** also facilitates use of communication devices and channels including, without limitation, email, cell phones, collaboration applications, and annunciator systems.

Language area **1110** also facilitates communication with additional data sources **1104**, such communication including, without limitation, information requests through search-oriented architectures, queries to the web through web agents, information requests to telematics devices/systems aboard trailers, trucks, and rail cars. Language area **1110** further facilitates two-way communication with warehouse robots (not shown).

In the exemplary embodiment, language area **1110** includes inner speech and thinking features **1112** that facilitate internal data flow within system **200** including, without limitation, data recall from the SDM features of memory sub-module **336** (shown in FIG. **3**) and organizing information perceived from real world **304** to solve problems and learn. Inner speech and thinking features **1112** also facilitate inner imagery, emotions, and memory functioning.

Also, in the exemplary embodiment, model **1100** includes a cognitive area **1120** that is closely associated with cognitive module **320** (shown in FIG. **3**). Cognitive area **1120** facilitates deliberation and action selection by system **200**. For example, in the context of an asset management application, for a number of available inputs, there may be several routes appropriate for the given conditions and destination match-ups. System **200** will choose the routes and/or load orders to suggest to the user.

Cognitive area **1120** also facilitates learning by system **200**. For example, in the context of an asset management

application, at the planner and receiver interface, system **200** can learn the name of the planner/receiver and the preferences of the planner/receiver using, without limitation, an avatar. Also, system **200** uses additional data sources **1104** to learn from the stream of information coming therefrom and uncover patterns in environmental conditions, e.g., without limitation, weather, traffic, and crime. Further, system **200** may use route-planning system features to learn which routes the customer rejects and build future routes that won't get rejected. Moreover, system **200** facilitates learning by warehouse robots, e.g., without limitation, the layout of the warehouse and the location of goods.

In the context of a supply chain management example, model **1100** facilitates cargo shipments from an origin to a destination. Planners use the planning interface at user interface **130**. The planners interact with a system-generated avatar to input the shipments details such as shipping time, shipping method, the origin, the destination. The avatar, in turn, interacts with the planner to verify information and to notify the planner of potential conflicts or inconsistencies.

System **200** requests additional information from the sources at its disposal, including, without limitation, memory sub-module **336** and additional data sources **1104** and transmits all to cognitive area **1120** through sensory input sub-module **306**. System **200** proposes an action plan **1130** that includes a proposed route that is transmitted to the planner at user interface **130**. In the exemplary embodiment, system **200** executes a pre-trip analysis using its decision making features **1131**. For example, system **200** will optimize fuel stops based on current prices. Also, the trip is compared to trips taken in the past, and then clustered with those trips in memory. Further, system **200** is able to learn the time it takes to make a specific trip, and generalize that information to predict the times for novel trips though the development of learned models.

The planner may reject **1132** the plan or accept the plan **1134**. If the plan is rejected **1132**, system **200** may request additional information from the planner, pull in additional information from sources **1104**, and/or propose **1130** a revised or new plan. The accepted plan **1134** is executed through execution process **1136** and action **1138** is performed, i.e., the cargo is loaded and shipped from the origin. At the warehouse, robots execute the load order utilizing technology that includes, without exception, RFID technology to locate the goods in the warehouse, and bring them to a designated area marked as a trailer.

While the shipment is en route, event interface **1102** and/or additional data sources **1104** updates system **200** with respect to the status of the shipment, the shipping means, and the shipping route using transmission of real-time dynamic data **1138** through subconscious agents **1140**. The data updates are evaluated by system **200**, and new important data **1142** will be evaluated to determine **1144** if any problems presented are easy to solve or hard to solve. Those problems that are easy to solve **1146** will be acted upon independently by system **200**. For example, system **200** facilitates in-vehicle decisioning through constant analysis of real-time information including, without limitation, weather, traffic, and the driver's behavior.

Those problems that are hard to solve **1148** will generate an alert **1150** that is transmitted **1152** to the planner and/or the receiver to obtain approval for the revision to the action plan generated by system **200**. In the exemplary embodiment, the revision is a revised ETA **1154**.

The revisions to the action plan due to dynamic conditions during the execution of the trip exhibit elements of artificial consciousness and general artificial intelligence (AGI). In general, AGI systems are flexible and adapt to changing rules, thereby facilitating adaption to, and learning from, dynamic environments and solving dynamic complex problems. Therefore, since system **200** exhibits elements of consciousness including, without limitation, a degree of self-awareness (system **200** understands the difference between self and non-self), the abilities to learn and adapt from/to its environment, have a general understanding of time (able to play scenes forward and backward in time), incorporate a wide range of background knowledge in its decisions, demonstrate intentionality and resourcefulness, have emotions.

The ability of system **200** to play scenes forward in time is related to the forecasting features of system **200**. As described above, system **200** generates a plurality of potential solutions in accordance with at least one predetermined goal of system **200** to ameliorate a dynamically determined condition based on at least one of real-time dynamic contextual data transmitted from at least one dynamic contextual data entity and at least one model formed and stored within system **200**. System **200** also generates at least one scenario for each of the solutions defining at least one string of forecasted real world events resulting from implementation of each of the solutions, wherein the forecasted real world events are at least one of possible and probable. System **200** further compares the strings of possible and probable forecasted real world events resulting from the implementation of each of the potential solutions. System **200** also selects at least one course of action from the potential solutions and transmits the at least one directive to at least one operative entity, thereby executing the at least one course of action.

The ability of system **200** to play scenes backward in time is related to the learning features of system **200**. System **200** determines a pattern of performance of system **200** by analyzing at least one of historical data and previously generated courses of action. System **200** also determines a pattern of performance by determining at least one real world effect resulting from executing the previously generated courses of action. System **200** may generate an emotional response to the at least one real world effect. System **200** also transmits the pattern of performance to adaptive on-line learning sub-module **340** (shown in FIG. **3**). Further, system **200** modifies a model **1040** (shown in FIG. **16**). Moreover, system **200** may modify at least one predetermined goal of system **200**, may generate at least one new goal, and/or may modify at least one potential solution in accordance with at least one of the modified goal and the new goal. Also, system **200** may modify at least one scenario for the potential solution and/or may generate at least one scenario for the potential solution. Further, system **200** may redefine at least one string of forecasted real world events resulting from actual implementation of each potential solution. Therefore, system **200** may use the learning features to reinforce use of existing courses of action that generate positive results and discourages use of courses of action that generate negative results.

System **200** includes a visual scheduler/execution display **1156** that displays the progress of the shipment as it completes the given route. In addition, display **1156** facilitates demonstrations of system **200** without waiting for the actual trailer to complete the route. Also, display **1156** will display changing conditions as a result of new events that may interfere with the trips, such as weather or traffic. Moreover, system **200** has the ability to carry out “what if?” exercises, i.e., scenarios of future events and actions can be mapped out even if no action is taken.

System **200** will execute a post-trip analysis based on data received, for example, without limitation, reporting based on fuel usage and engine idle time. Also, if either of fuel usage or

engine idle time exceeds predetermined parameters, system **200** will store such information and apply it to subsequent similar trips.

System **200** is scalable, i.e., in some alternative embodiments, system **200** may be scaled downward to execute tasks for a larger system. Such a scaled-down system will only require selected data that affects the plan, rather than a continuous stream of data.

The above-described computer-implemented systems with adaptive learning provide a cost-effective method for facilitating increased reliability and decreasing disruptions of enterprise operations. Specifically, the systems and methods described herein provide for flexible and adaptive systems for the solution of highly complex and dynamic problems. The systems and methods described herein initiate, facilitate, and direct physical and tangible effects in the real world through transmission of directives to operative entities in the real world, such directives being a result of either autonomic or cognitive operation. Also, the systems and methods described herein provide for receipt of real world, real-time feedback induced by the directives, including internal data of a feed-forward, i.e., anticipatory nature. Further, the systems and methods described herein provide for the systems perceiving an episodic sense of time through perception of events and storing memories of such events. Moreover, the systems and methods described herein provide for distinguishing between positive outcomes and negative outcomes and generating an emotional response to real world effects generated as a result of executing a course of action.

Also, the systems and methods described herein utilize memory in a software-configured SDM configuration that substantially models human memory to facilitate learning, pattern recognition, and self-guided decision capabilities. Further, the systems and methods described herein facilitate adaptive on-line learning through receipt of dynamic contextual data associated with external events and conditions while interacting with the real world and using self-adapting, learning, and problem solving mechanisms. Moreover, the systems and methods described herein facilitate communication between the adaptive cognitive system and other systems and devices to share knowledge and data therebetween.

Furthermore, the systems and methods described herein utilize deliberation to compare potential solutions, select at least one course of action from such potential solutions, and transmit such course of action to generate and transmit directives to operative entities to execute the course of action in the real world.

An exemplary technical effect of the methods and computer-implemented systems described herein includes at least one of (a) enabling initiation of, facilitation of, and direction of physical and tangible effects in the real world through transmission of directives to operative entities in the real world, such directives being a result of either autonomic or cognitive operation; (b) enabling receipt of real world, real-time feedback induced by system-generated directives, including internal data of a feedforward, i.e., anticipatory, nature; (c) enabling the systems’ perceiving an episodic sense of time through perception of events and storing memories of such events; (d) enabling the systems to distinguish between positive outcomes and negative outcomes and generate an emotional response to real world effects generated as a result of executing a course of action; (e) enabling the systems to substantially models human memory to facilitate learning, pattern recognition, and self-guided decision capabilities through utilizing memory in a software-configured SDM configuration; (f) enabling the systems to facilitate adaptive on-line learning through receipt of dynamic contextual data associated with external events and conditions while interacting with the real world and using self-adapting, learning, and problem solving mechanisms; (g) enabling communication between the adaptive cognitive system and other systems and devices to share knowledge and data therebetween; and (h) enabling deliberative features of the system to compare potential solutions, select at least one course of action from such potential solutions, and transmit such course of action to generate and transmit directives to operative entities to execute the course of action in the real world.

Exemplary embodiments of computer-implemented systems with adaptive learning features and methods for operating such systems are described above in detail. The computer-implemented systems and methods of operating such systems are not limited to the specific embodiments described herein, but rather, components of systems and/or steps of the methods may be utilized independently and separately from other components and/or steps described herein. For example, the methods may also be used in combination with other enterprise systems and methods, and are not limited to practice with only the asset management and supply chain management systems and methods as described herein. Rather, the exemplary embodiment can be implemented and utilized in connection with many other enterprise applications.

Although specific features of various embodiments of the invention may be shown in some drawings and not in others, this is for convenience only. In accordance with the principles of the invention, any feature of a drawing may be referenced and/or claimed in combination with any feature of any other drawing.

This written description uses examples to disclose the invention, including the best mode, and also to enable any person skilled in the art to practice the invention, including making and using any devices or systems and performing any incorporated methods. The patentable scope of the invention is defined by the claims, and may include other examples that occur to those skilled in the art. Such other examples are intended to be within the scope of the claims if they have structural elements that do not differ from the literal language of the claims, or if they include equivalent structural elements with insubstantial differences from the literal language of the claims.

What is claimed is:

1. A computer-implemented system comprising:

an edge module;

at least one input device coupled to said edge module, said at least one input device configured to generate data input signals; and

a cognitive module coupled to said edge module, said cognitive module comprising:

a perception sub-module coupled to said edge module, said perception sub-module configured to receive the data input signals;

a learning sub-module coupled to said perception sub-module, said learning sub-module configured to adaptively learn at least in part utilizing the data input signals;

a memory sub-module configured to store a plurality of models formed within said learning module from a plurality of data clusters formed within said learning module; and

a problem solving sub-module coupled to each of said perception sub-module, said memory sub-module, and said learning sub-module, said problem solving sub-module configured to generate at least one potential solution in accordance with at least one predetermined goal of said system to ameliorate a condition based on at least one of the data input signals transmitted from said perception sub-module and at least one of said plurality of models, wherein said cognitive module further comprises an internal thinking sub-module coupled to said problem solving sub-module said internal thinking sub-module configured to generate at least one scenario defining at least one string of forecasted real world events resulting from implementation of a course of action selected from said at least one potential solution, wherein said forecasted real world events are at least one of possible and probable.

2. The computer-implemented system in accordance with claim **1**, wherein said system further comprises an asset management system.

3. The computer-implemented system in accordance with claim **1**, wherein said learning sub-module is further configured to:

generate a plurality of data clusters, each of said plurality of data clusters is defined at least in part utilizing at least one attribute; and

form at least one model from at least a portion of said plurality of data clusters.

4. The computer-implemented system in accordance with claim **1**, wherein said cognitive module further comprises at least one communication channel coupled to said internal thinking sub-module and coupled to at least one input entity, said at least one communication channel configured to:

transmit real world data to said internal thinking sub-module, wherein at least some of the real world data is static and dynamic data, wherein at least some of the static data is static contextual data and at least some of the dynamic data is dynamic contextual data; and

communicate with other systems to share knowledge and data therebetween.

5. The computer-implemented system in accordance with claim **1**, wherein said cognitive module further comprises:

a deliberation sub-module coupled to said problem solving sub-module and said perception sub-module, said deliberation sub-module configured to:

compare a plurality of potential solutions transmitted from said problem solving sub-module; and

select at least one course of action from said plurality of potential solutions, and

an action sub-module coupled to said deliberation sub-module, said action sub-module configured to transmit directives to at least one operative entity to execute said at least one course of action in the real world.

6. The computer-implemented system in accordance with claim **5**, wherein:

said perception sub-module is further configured to receive feedback from said at least one input entity;

said learning sub-module is further configured to modify at least one of said plurality of models at least in part utilizing the feedback, thereby defining at least one modified model; and

said problem solving sub-module is further configured to at least one of generate a new solution and modify an existing solution as a function of said at least one modified model.

7. The computer-implemented system in accordance with claim **6**, wherein said edge module comprises at least one of:

a sensory input sub-module comprising said at least one input entity;

a reflex sub-module coupled to said sensory input sub-module, said reflex sub-module configured to generate at least one autonomic response to input signals transmitted from said at least one input entity, thereby bypassing said cognitive module; and

said action sub-module further coupled to said reflex sub-module, said action sub-module further configured to transmit directives to at least one operative entity to execute at least one predetermined course of action as a function of said at least one autonomic response.

8. The computer-implemented system in accordance with claim **1**, wherein said cognitive module further comprises a comparison sub-module and an emotion sub-module, wherein said comparison sub-module, said learning sub-module, and said memory sub-module cooperate to with said emotion sub-module to:

distinguish between positive outcomes and negative outcomes; and

modify at least one of said plurality of models based on at least one of the positive outcomes and the negative outcomes.

9. A method of using a computer-implemented system having adaptable cognitive features, said method comprising executing instructions stored on a computer-readable medium comprising:

generating a plurality of potential solutions in accordance with at least one predetermined goal of the computer-implemented system to ameliorate a dynamically determined condition based on at least one of real-time data inputs transmitted from at least one data input entity and at least one model formed and stored within the computer-implemented system;

generating at least one scenario for each of the plurality of solutions defining at least one string of forecasted real world events resulting from implementation of each of the plurality of solutions, wherein the forecasted real world events are at least one of possible and probable;

comparing the strings of possible and probable forecasted real world events resulting from the implementation of each of the plurality of potential solutions to each other;

selecting at least one course of action from the plurality of potential solutions based at least in part on the comparison;

transmitting at least one directive associated with the at least one course of action to at least one operative entity, thereby executing the at least one course of action; and

generating an emotional response to real world effects generated as a result of executing the at least one course of action comprising:

distinguishing between at least one positive outcome and at least one negative outcome; and

modifying at least one of a plurality of models based at least in part on at least one of the at least one positive outcome and the at least one negative outcome.

10. The method in accordance with claim **9**, wherein generating a plurality of potential solutions comprises:

generating a plurality of data clusters, wherein each of the plurality of data clusters is defined at least in part with respect to at least one attribute; and

forming at least one model from at least a portion of the plurality of data clusters.

11. The method in accordance with claim **10**, wherein forming at least one model comprises forming a plurality of models, said method further comprising:

receiving feedback from at least one input entity, wherein at least a portion of the feedback is real world data, and at least a portion of the real world data is static and dynamic data, wherein at least some of the static data is static contextual data and at least some of the dynamic data is dynamic contextual data;

modifying at least one of the plurality of models based at least in part on the feedback, thereby defining at least one modified model; and

at least one of generating a new solution and modifying an existing solution as a function of the at least one modified model.

12. The method in accordance with claim **11** further comprising:

generating at least one autonomic response to the feedback received from the at least one input entity; and

transmitting at least one directive to at least one operative entity, thereby executing at least one predetermined course of action as a function of the at least one autonomic response.

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